Cross-Income Exposure in Schools and Long-Run Student Outcomes*

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Abstract

I examine how economic segregation in schools affects students' economic mobility using rich administrative data from Texas. Lower-income students are exposed to nearly ten times fewer upper-income classmates than wealthier peers. To isolate peer effects, I exploit within-school, between-cohort variation in the share of upper-income students, controlling for school trends. Greater exposure to upper-income peers increases four-year college enrollment and wages for lower-income students. These effects are driven by exposure to lower-achieving upper-income peers. Exposure to lower-income peers has no detectable impact on their wages, suggesting that promoting cross-income exposure may improve equity with minimal costs.

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1 Introduction

An important goal of education is economic mobility, but the likelihood of a U.S. child earning more than their parents has declined in recent decades (Chetty et al., 2017). One factor long theorized to relate to economic mobility is social capital, defined as relationships with others that enable individuals to access resources (Bourdieu, 1986; Coleman, 1988).[1] Most recent work suggests that friendships with higher-income individuals (cross-income social capital) account for a substantial portion of the variation in economic mobility across neighborhoods (Chetty et al., 2022). However, we know little about how institutional structures, such as schools, shape students' opportunities to form those relationships and why exposure to upper-income peers might matter for economic mobility.

To my knowledge, this is the first study to document the cumulative classroom exposure of lower-income students to higher-income peers throughout middle and high school. It is also the first to estimate the impact of peer family income in secondary school—specifically, the share of higher-income classmates on lower-income students' long-run outcomes, including college enrollment and early-career wages. The analysis leverages rich administrative data from Texas, a demographically representative and large US state, which allows me to link student records—including student classroom assignment and test scores—to postsecondary and labor market outcomes. I find that lower-income students are exposed to significantly fewer higher-income classmates than their wealthier peers, largely due to residential and school-level socioeconomic segregation rather than within-school classroom assignment.[2] Finally, using within-school, between-cohort variation in the share of upper-income students, I show that lower-income students in cohorts with greater exposure to higher-income peers are more likely to enroll in college and earn higher wages in early adulthood. I also provide suggestive evidence that peer income may affect students through channels distinct from peer academic achievement.

I use "lower income" and "higher/upper income" as shorthand for students who are always below the free/reduced lunch income eligibility cutoff (income below $51,338 for a family of four) and

1. Social capital theory has been applied in education and employment to identify the drivers of inequities (e.g., Bourdieu, 1986; Coleman, 1988; Fernandez and Fernandez-Mateo, 2006; De Giorgi, Pellizzari, and Redaelli, 2010; Schmutte, 2015).

2. This finding aligns with Owens, Reardon, and Jencks (2016), who estimate that roughly two-thirds of income-based school segregation reflects segregation between school districts. However, their analysis did not include classroom-level data and thus could not assess the role of within-school sorting.

those who are always above the free/reduced lunch eligibility cutoff, respectively. Upper-income students constitute approximately 24% of students enrolled in public schools in Texas.[3] In the descriptive portion of this paper, I define exposure to upper-income students as the share of a student's cumulative number of classmates between grades 5 and 12 who are upper income. I find that the median lower-income students' share of upper-income classmates is 6% compared to 51% for the median upper-income student, and one in every five lower-income students goes through schooling with a share of upper-income classmates smaller than 1%.[4]

To address selection concerns and isolate the role of peers independent of access to resources, I exploit variation in peer composition across adjacent cohorts within the same school, controlling for school trend. Here, unlike in the descriptive portion of the paper, I use a sample of ten cohorts of high school students so that I am able to follow them into adulthood. The temporary (small) changes in a cohort's share of upper-income peers in a school are less likely to impact students' access to school resources and so can capture if there are peer family income spillovers that are independent of access to school resources (e.g., passage of institutional knowledge) that impact lower-income students' long-term outcomes. Consistent with this, I find that residual variation in peer income has no (detectable) impact on lower-income students' proportion of novice teachers, number of advanced courses offered, and average school per-pupil spending.

It is important to disentangle peer family income spillovers from access to observable school resources. If the positive relationship we observe between the share of upper-income peers and lower-income students' outcomes is driven only by differences in access to school resources (e.g., classrooms with more upper-income students tend to have more experienced teachers), then policies that equalize access to resources could improve outcomes without reducing economic segregation. If, however, the effects operate through peer income spillovers—independent of observable resource differences—then addressing school economic segregation would be necessary to improve outcomes for lower-income students.

I find that a 10-percentage-point increase in the share of upper-income classmates increases lower-

3. The income cutoffs described are based on free/reduced lunch income eligibility in 2022. This definition of economic disadvantage builds on Michelmore and Dynarski (2017), who find that the number of years on free/reduced lunch captures student economic disadvantage better than a binary measure of economic disadvantage based on one year of free/reduced lunch eligibility status. Among students for whom financial aid data are available, I find that those with lower and higher incomes have a median parental income of approximately $23,033 and $131,294, respectively.

4. The median lower-income student goes through grades 5 to 12 having met 39 upper-income students out of around 700 (unique) students, compared to 325 upper-income students for the median upper-income student.

income students' likelihood of enrolling in a four-year public college by 0.5 percentage points (3.6% increase) and raises their early adult wages by 2.1%. The observed increase in quarterly wages is around three times the estimated return to 4-year college enrollment based on Zimmerman (2014), suggesting that the impact on wages likely does not operate exclusively through 4-year college enrollment. The positive impact of marginal, temporary changes in the share of upper-income students on lower-income students' wages suggests that resource equalization policies alone may be insufficient to address the harms of economic segregation.

The impact of the share of upper-income students is consistent when controlling for various measures of peer achievement, suggesting that upper-income peer spillovers on lower-income students are independent of upper-income students' academic achievement.[5] If anything, the positive impact of having a higher share of upper-income students appears to be driven by upper-income lower-achieving students. This result challenges the common focus on peer academic spillovers as the primary mechanism in the education production function and suggests a broader role for other potential social capital mechanisms: the transmission of institutional knowledge, norm-setting, or enhanced aspirations through economically advantaged peers. Prior work on peer effects in k-12 has generally focused on peer academic achievement (see, e.g., Imberman et al, 2012; Lavy, Paserman and Schlosser, 2012; Jackson, 2013; Feld and Zoelitz, 2017). That said, the evidence I present on the role of peer achievement is only suggestive. More conclusive evidence requires a better instrument for peer achievement as peer achievement may be impacted by peer income in earlier cohorts. I try to address the potentially endogeneity of peer achievement by using earlier student achievement data, but the earliest we have test score data is in 3rd grade.

Lastly, I test whether increased exposure to lower-income peers adversely affects upper-income students. I find that a 10 p.p. increase in the share of lower-income students (holding constant the proportion of middle-income students, i.e. swapping upper-income students with lower-income students) slightly decreases upper-income students' likelihood of graduating from college (1.7% ($p = 0.05$)), though this does not seem to be reflected in their wages–I find no detectable impact on upper-income students wages (-0.9% ($p = 0.3$)). The small null impact on wages highlights the possibility that policies designed to improve cross-income exposure could be efficiency-enhancing—or at least

5. The coefficient on the proportion of upper-income students is slightly larger when controlling for peer achievement.

neutral—–helping lower-income students without imposing significant costs on their higher-income peers.

I complement my administrative data analysis with high school-level measures of cross-income friendship networks from Chetty et al. (2022) and student-level friendship data from the Add Health study. These comparisons show that school-level exposure to upper-income peers is highly predictive of both school-level economic connectedness and friending bias, as well as individual-level friendship formation across income groups.[6]

This paper makes three main contributions. First, it's the first to my knowledge to quantify how economic segregation across districts, schools, and classrooms drives large differences in exposure to upper-income classmates across students, using detailed classroom rosters over time. The segregation literature has focused primarily on racial/ethnic segregation (e.g., Clotfelter, Ladd, and Vigdor, 2002; Clotfelter, Ladd, Clifton and Turaeva, 2021) and academic sorting within schools (e.g., Antonovics, Black, Cullen, and Meiselman, 2022; Lucas and Berends, 2002). The limited work on economic segregation is hampered by multiple data limitations, including a lack of observations on students within a classroom and/or on their college enrollment and employment outcomes (Owens, Reardon and Jencks, 2016; Dalane and Marcottee, 2022; Kalogrides and Loeb, 2013). I also show that classroom measures of cross-income exposure, derived from administrative data, can be used as close proxies for cross-income social capital, as captured by Facebook friendship data.

Second, it's the first paper to my knowledge to try to isolate the role of peer income spillovers in secondary school on lower-income students' college enrollment and wages using idiosyncratic variation in the share of upper-income peers, and its relation to peer achievement spillovers. I contribute to the large peer effects literature examining the relationship between peer composition and short- and long-term outcomes (examples include Sacerdote, 2001, 2011; Zimmerman, 2003; Lavy, Paserman and Schlosser, 2011; Black, Devereux and Salvanes, 2013; Cools, Fernandez and Patacchini, 2019; Zimmerman, 2019; and Rao, 2019). This paper is most closely related to work by Cattan, Salvanes and Tominey (2022), which investigates the impact of exposure to the children of parents who attended elite schools in Norway. I extend Cattan, Salvanes and Tominey (2022)

6. The correlation between exposure to upper-income classmates as measured in this paper and economic connectedness as measured by Chetty et al. (2022) is 0.9. Friending bias as measured by Chetty et al. (2022) is the likelihood of befriending high-SES students conditional on school composition. I find that friending bias in schools is highly correlated with the level of sorting by income across classrooms in a school: the correlation is approximately 0.6.

work in two key ways. First, I quantify how common cross-income exposure is in middle and high school classrooms and decompose how much of that exposure arises from segregation at the district, school, and classroom levels. Second, I identify the impact of exposure to upper-income peers on students' wages—effects that may not necessarily operate through parents' education and that Cattan, Salvanes, and Tominey (2022) were not able to capture. I show that the wage effects are larger than what would be predicted based on the impact on college enrollment alone, suggesting that peer income spillovers may operate through additional mechanisms beyond higher education pathways.

The paper is organized as follows. In Section 2, I begin by laying out the theoretical framework of the analysis. Section 3 defines my measures of cross-income exposure and data used. Section 4 reports estimates of cross-income exposure at the state level and how they compare to cross-test score exposure, as well as district, school and classroom integration benchmarks. Section 5 describes the relationship between exposure to upper-income students and friendship formation. Section 6 reports the relationship between cross-income exposure and long-term student outcomes. Section 7 concludes the paper.

2 Conceptual Framework

Exposure to upper-income peers is a function of the district a student resides in, the school they enroll in, and the classroom they are assigned to or choose. At each of these levels, parents and students make decisions about where to live and what school and classroom to enroll in given their economic resources (household income) and subject to potential information imperfections and discriminatory barriers. These decisions and constraints shape not only their exposure to upper-income peers but also their access to neighborhood and school resources. The first part of the paper attempts to draw a complete picture of how each of these layers (district, school, and classroom) contributes to lower-income students' exposure to upper-income peers across schooling years.

Theoretically, exposure to upper-income peers could shape lower-income students' long-term outcomes in at least two ways: resource allocation and/or social capital.[7] The distribution of

7. Other potential channels include classroom spillover and class rank (Cattan, Salvanes, and Tominey, 2022).

students by income across and within schools could shape how financial and instructional resources are allocated (Owens and Candipan, 2019 and Kalogrides and Loeb, 2013). Owens and Candipan (2019) find that schools in upper-income neighborhoods tend to have higher spending per student and higher salaries for teachers. Unequal resource allocation can also take place within a school, between classrooms. Kalogrides and Loeb (2013) find that upper-income students tend to be assigned more experienced teachers than lower-income students in the same school. I find a similar pattern in Texas. Students with 10 p.p. more upper-income classmates, within the same school, are in classrooms with 3 p.p. fewer novice teachers (with three or less years of experience), on average.[8]

Another potential channel through which exposure to upper-income peers might matter is social capital. Social capital may impact students' long-term outcomes through information and/or norm setting (Coleman, 1988). An example of an information channel is if higher-income students are more likely to know which courses to take to improve their likelihood of being accepted into more selective colleges and that they are more likely to share this information with lower-income students when sharing the same classroom.[9] The social norms channel depends on the prevalence (actual/assumed) of a behavior in a group. For example, if upper-income students are more likely to enroll in selective universities, this may create a norm/expectation that students apply and enroll in selective universities across income groups.[10]

The strength of the information and norm channels may depend on the school and social structure. If upper- and lower-income students are likely to attend different classrooms (because of high classroom sorting by income/test score), then they may be less likely to pass on information and shape cross-group norms.[11] It may also depends on the strength of the cross-group relationships. If students are less likely to form friendships across income categories, then they may be less affected by cross-income exposure. Hoxby (2001) finds that peer achievement effects are stronger within

8. The raw relationship between the share of upper-income classmates and access to school resources is summarized in Figures A19 and A20 in the Supplementary Appendix. The relationship between advanced course taking and exposure to upper-income students is more ambiguous, although generally positively correlated with exposure to upper-income students. In contrast, school spending per pupil is negatively correlated with higher exposure to upper-income students.

9. Bourdieu (1986) suggests that individuals from upper-income households have higher cultural capital (knowledge, skills, and tastes belonging to a social class), which results in the persistence and reproduction of social structures.

10. Papers that documented the potential importance of social norms on academic performance in schools, perceptions, and giving behavior include Frey and Meier (2004), Bursztyn and Jensen (2015), Bursztyn, González, and Yanagizawa-Drott (2020).

11. I find that changes in cohort income composition are not perfectly reflected in changes in lower-income students' classroom peer composition, suggesting that sorting within a school across classrooms may reduce the impact of increases in a schools' cohort income composition.

a race. Cattan, Salvanes, and Tominey (2022) find that the impact of classmates whose parents graduated from elite schools is stronger among high-SES students than among low-SES students, suggesting that peer effects may be weaker across income groups. I present evidence in section 6 suggesting that exposure to upper-income peers of the same race/ethnicity may have a larger impact on lower-income students.

Alternatively, the social capital channel may operate exclusively through students' academic achievement. In other words, it could be that upper-income students happen to perform better academically, and being around higher achieving students–independent of their income–has an impact on lower-income students' academic performance and labor outcomes. Some of the channels through which a higher proportion of higher achieving peers may impact student outcomes include: student class rank, teacher behavior and/or academic spillover through peer-to-peer tutoring. The peer effects literature suggests the impact of peer achievement may vary depending on students' own baseline academic performance (Cools, Fernández and Patacchini, 2019; Feld and Zölitz, 2017, Lavy, Paserman and Schlosser, 2011; Sacerdot, 2011).

The type of variation I use in the causal analysis (Section 6)—small, temporary deviations from a school's average peer composition—may not be large enough to alter classroom norms or school resources. However, such variation may affect the amount of information available to lower-income students, shaping their college choices and employment outcomes. In this paper, I focus on changes in the share of upper-income peers, which do not necessarily translate directly into cross-income relationships (social capital). That said, in Section 5 I show that the share of upper-income peers in a school is strongly predictive of the likelihood of forming cross-income friendships.

3 Data and Measures of Cross-Income Exposure

3.1 Data

I use longitudinal administrative data from the Texas Education Research Center (ERC) that link student data from the Texas Education Agency (TEA) to Texas Higher Education Coordination Board (THECB) and Texas Workforce Commission (TWC) data. These TEA data cover the period from 2004 to 2022 and include student test scores, courses (and class assignment starting in 2011), demographics, attendance, graduation, and assigned teachers (including teacher certification and demographics). My main measure of income is free/reduced lunch status. I use years of assignment to free/reduced lunch status to capture the degree of economic disadvantage.[12]

I use college enrollment data (THECB) from 2014 to 2023 data. I focus on the following college enrollment outcomes: any college enrollment, 2-year public college enrollment, 4-year public college enrollment, highly selective college enrollment, and graduation from any college.[13] I also use financial aid application data to identify parental income. The college data are limited to enrollments in the state of Texas. The employment data (TWC) includes information on industry, employment level, and Quarterly wage. The employment data are based on unemployment insurance data and hence cover only employment in Texas. In Section 6, I use quarterly wage data from 2023 (the most recent employment data).

To identify and better understand the link between exposure and friendship formation, in Section 5, I supplement the analysis with two other sources of data: Add Health data and publicly available high school measures of the likelihood of cross-income friendship based on Facebook data from Chetty et al. (2022), both of which I discuss in more detail in Section 5.

3.2 Measure of Family Income and Cross-Income Exposure

To measure student income, ideally, I would have parental income for every enrolled student. In the absence of data on parental income, I use the proportion of years on free/reduced lunch to capture the degree of economic disadvantage.[14] I divide students into three main income groups: always, sometimes and never on free/reduced lunch. I define upper-income students as those never in free/reduced lunch status. Upper-income students represent approximately 24% of the student population. Students always in free/reduced lunch status (lower-income students) constitute approximately 29% of the student population.

The segmentation of students by the proportion of years eligible for free or reduced-price lunch appears to capture meaningful variation in parental income, as shown in Figure 1. Among students

12. Test scores are mainly based on standardized grade 4 and 8 TAKS (2007–2011) and STAAR (2012–2018) reading and math tests.

13. Colleges are defined as selective if they are between levels 1 and 4 based on Barron's selectivity index (most to very competitive in 2009).

14. To identify the proportion of years on free/reduced lunch, I use all years from 2004 to 2022.

with financial aid data, the median reported parental income is $131,294 for those never eligible, $42,879 for those sometimes eligible, and $23,033 for those always eligible. Because the financial aid data reflect parental income at a single point in time (the end of secondary school, just before college entry), they may be sensitive to temporary income shocks and may not represent permanent or long-term parental income. Students with financial aid data are also a select, systematically different, group.[15] Nevertheless, it can provide us with a general sense of the variation and is likely an upper bound for students who are always on free/reduced lunch and a lower bound for students on never on free/reduced lunch status since students with high parental income are less likely to apply for financial aid as they are likely ineligible.[16]

For the rest of the paper, I refer to students who are never on free/reduced lunch as higher- or upper-income. I refer to students who are sometimes and always on free/reduced lunch as middle- and lower-income students, respectively. This paper focuses on lower-income students' exposure to upper-income peers and how it relates to their long-term outcomes.

I define cross-income exposure as the share of classmates of another income group in a student's classroom, focusing on the share of upper-income students. I capture the cumulative exposure to upper-income students by following three cohorts of students (2012–2014) starting from fifth to expected twelfth grade in Texas. In each year, I capture the number of classmates in a student's classroom (excluding self). I also capture the number of upper-income classmates in the classroom (excluding own status). I divide the total number of upper-income peers student i encountered in all the classrooms they were enrolled in between grades five and twelve ($N^H_{(-i)}$) by the total number of peers student i encountered in those classrooms ($N_{(-i)}$): $\frac{N^H_{(-i)}}{N_{(-i)}}$.

One can understand this measure as capturing the proportion of potential interactions rather than the proportion of students. If a student is in multiple classrooms with the same student, the latter is included in the denominator (total student interactions) multiple times. She would also be included in the numerator if she were of upper income multiple times. The assumption is that what matters is the proportion of interactions rather than the proportion of students. Each interaction

15. Financial aid data are available for 51%, 40% and 34% of students who are never, sometimes, and always in free/reduced lunch status, respectively.

16. For students who apply to public universities in Texas and report parents' income bracket, 81% 24% and 3% who were never, sometimes and always on free/reduced lunch, respectively, report having parental income above $80,000. 33%, 18% and 4% of students who are never, sometimes and always on free/reduced lunch apply to public universities in Texas and report parental income bracket, respectively.

is likely to yield an additional benefit. I assume that each interaction has an equal level of benefit.

4 Descriptive Patterns: How Likely is Cross-Income Exposure and What is the Contribution of District, School and Classroom Economic Segregation?

4.1 Sample

To capture students' exposure to upper-income classmates, I follow three cohorts of students from grade 5 to expected grade 12. The three cohorts are the 2012, 2013 and 2014 cohorts. Students enrolled in any public school (including charter schools) in Texas in grade 5 in academic year 2012 belong to the 2012 cohort. These cohorts of students are followed in the data, and their classroom income composition is documented every year from 2012 to 2019. Across these cohorts, there are 1,128,554 students. Table 1 summarizes the characteristics of the sample. Approximately 50% of the cohort identify as Latin-American students, 14% as Black students, and 68% as White students. Most of the students are enrolled in traditional public schools—4–6%, in a given grade, are enrolled in a charter school, as shown in Table A1. Note that "expected" grade is not their actual grade but the grade in which we expect them to be enrolled given the year and their cohort.

4.2 Descriptive Patterns of Exposure to Upper-Income Students

Lower income students go through schooling sharing very few classrooms with upper-income classmates. The average lower-income student goes through grades five to twelve with 10% of their classmates upper-income compared to 51% of upper-income students' classmates as shown in Figure 2. A large proportion of lower income students are exposed to a small number of upper-income students—the distribution of exposure to upper-income peers is right skewed, as shown in Figure 4 Panel (a). The typical (median) lower-income student is in classrooms with 6% upper-income students and for one in every five lower-income students 1% of their classmates are upper income. The median lower-income student goes through grades 5 to 12 having met 39 upper-income students out of around 700 students, compared to 325 upper-income students for the median upper-income student.[17]

17. This statistic is based on a random sample of 3000 students (1000 from each cohort) for whom I only weighted their first interaction (first classroom shared) with a given upper-income student. The difference in exposure between upper- and

These patterns are not explained by racial and ethnic segregation. Lower-income students in all racial/ethnic groups are exposed to fewer upper-income students than their upper-income counterparts as shown in Figure A5.[18] I also find gaps in exposure to same race/ethnicity upper-income classmates within racial and ethnic groups as shown in Figure A6, though the gap is smaller.[19]

The finding that lower income students are exposed to relatively very few upper-income classmates is consistent using other definitions of upper- and lower-income students. I find that the average Lower-income student goes through schooling with 13% of their classmates with financial aid data having reported parental income in the top 24 percentiles, compared to 43% of upper-income students' classmates as shown in Figure A1.[20]

The difference in exposure to upper-income students is a function of residential, school, and classroom socioeconomic segregation. To identify how each of residential economic segregation, school segregation and classroom assignment contribute to exposure to upper-income peers I compare students' exposure to upper-income students to three benchmarks. In the first benchmark, students enrolled in the state are randomly assigned to districts, schools, and classrooms (district integration benchmark). In the second, the district composition is fixed, and students are randomly assigned to schools and classrooms (school integration benchmark). In the third, the school composition is fixed, and students are randomly assigned to classrooms (classroom integration benchmark). In practice, this is very similar to comparing lower-income students' average exposure to upper-income students to the proportion of upper-income students in the state, district and school. For example, if we were to randomly assign students across districts, the expected exposure to higher-income students would be equal to the proportion of higher-income students enrolled in the state of Texas.[21]

I show these benchmarks in Figure 2 with students' actual exposure to upper-income classmates. The difference between actual exposure and the district benchmark for full integration is

lower-income students based on weighting only the first interaction is similar at 39 p.p.. Lower-income students living in urban districts are exposed to the smallest share of upper-income students (8%) and the gap in exposure to upper-income students between upper- and lower-income students is largest in suburbs as shown in Figure A2.

18. White students across incomes are exposed to approximately 10 percentage points more upper-income classmates.

19. The low exposure of Hispanic and Black, lower-income students to upper-income classmates of the same race/ethnicity is concerning if peer effects are stronger within racial groups.

20. The financial aid data may underestimate the gap in exposure because of left and right-tale missing data. Classmates' average parental income based on financial aid data is $47,152 and $108,859 on average, for lower- and upper-income students, respectively.

21. Since I am excluding own status, the expected exposure for higher- and lower-income students under random assignment will be slightly different; higher-income students would be exposed to fewer higher-income peers since their own status is not included in the numerator. This matters more in small units such as school classrooms. I present my calculation of expected exposure under random assignment—excluding students' own status—in Supplementary Appendix A.

11.6 percentage points. In other words, had students been randomly assigned to districts, lower-income students would have been in classrooms with 11.6 percentage points more upper income classmates—that is more than twice lower-income students' current exposure. The difference between actual exposure and the school benchmark for full integration is 3.4 percentage points, and the difference between actual exposure and the classroom benchmark for full integration is 0.7 percentage points.[22] The relatively large difference between the district and school integration benchmarks is consistent with the findings of Owens, Reardon, and Jencks (2016), who report that approximately two-thirds of income segregation between schools is due to segregation between districts. However, Owens, Reardon, and Jencks (2016) did not have classroom level data and so were not able to quantify the role of the classroom.

The small difference between actual exposure and the classroom integration benchmark suggests that, for the average lower-income student, classroom assignment accounts for a very small portion of the low exposure to upper-income students. However, school classroom-level policies may be easier to implement, and popular district-level policies such as the addition of charter schools appear to have an even smaller impact on cross-group exposure.[23]

The large contribution of residential and school socioeconomic segregation on students' exposure to upper-income peers would prompt us to think of policies that focused on greater district and school integration (e.g., racial integration policies such as Metropolitan Council for Educational Opportunity (METCO)'s voluntary busing program in Boston and race-based busing in Charlotte-Mecklenburg schools). However, district (or school) integration policies may prompt districts (or schools) to track students by income into different schools (or classrooms). I find that districts that are more integrated do not fully capture the benefit of having a higher share of upper-income students. Classroom integration becomes increasingly important in higher-income districts as shown in Figure A9.[24]

Low exposure to upper-income students is a function of both who enrolls in a district/school and how districts and schools are organized. Two districts (or schools) could have the same proportion

22. A school's proportion of upper-income students overestimates lower-income students' exposure to upper-income students, on average. 67% of lower-income students, compared to 30% of upper-income students, are exposed to fewer upper-income classmates than would be expected had students been randomly assigned to classrooms.

23. Monarrez, Kisida, and Chingos (2022) find that a charter school opening decreases the exposure of Black and Hispanic students to White and Asian students by approximately 0.3 and 0.1 percentage points, respectively.

24. Setren (2024) finds that METCO improved bussed minority students' test scores and college enrollment and that bussed students were tracked in receiving schools to lower-performing classes.

of upper-income students, but in one district (or school) lower-income students are exposed to fewer upper-income students because they attend different schools (or classrooms). I find that districts with more charter and private schools relative to the number of students served tend to have higher levels of between-school sorting by income. I also find that the number of science and math courses offered in a school correlates most strongly with classroom sorting by income, regardless of whether those courses are advanced. In other work, using variation in the timing of when an advanced course is added to a subject area, I find that the addition of an AP course increases lower-income students exposure to upper-income classmates driven by a rise in the overall share of upper-income students at the school, offsetting increases in sorting by income (Mallah, 2024). See Supplementary Appendix B for more details.

4.3 Exposure to Upper-Income Students Compared to Exposure to Higher-Achieving Students

The difference in exposure to upper-income students may capture differences in exposure to higher-performing students. Understanding how the relationship between exposure to upper-income students compares to exposure to higher-achieving students has practical and policy implications. If exposure to upper-income students is analogous to exposure to higher-achieving students, then it would be difficult to disentangle the spillover from having upper-income peers from having higher-achieving peers, and income desegregation policies may address both gaps in exposure to upper-income and higher-achieving students. If instead peer income and achievement compositions capture two different phenomena, then we could identify the impact of each on students' long-term outcomes separately, and interventions that address gaps in peer achievement would be different from those that address gaps in peer income.

The difference in exposure to higher-achieving students between upper- and lower-income students is considerably smaller than the difference in exposure to upper-income students. I define higher-achieving students as students who scored in the top 24 percentiles of reading test scores in grade 4 so that it is comparable to the proportion of students who are upper income (24% of students are upper income).[25] As shown in Figure 3, lower-income students are exposed to 20 percentage

25. Similar patterns if I define higher-achieving students by their grade 4 math test scores.

points fewer higher-achieving students between grades 5 and 12 than higher-income students. In comparison, the gap in exposure to upper-income students is closer to 41 percentage points.[26]

Students are more clustered by income than by test score. The distribution of exposure to upper-income students is right-skewed, but exposure to higher-achieving students is normally distributed as shown in Figure 4 Panel (b): Lower-income students at the 25th percentile of the peer income distribution are exposed to 1.4% upper-income classmates. In comparison, lower-income students at the 25th percentile of the peer achievement distribution are exposed to 12% high-achieving classmates.[27]

5 How Does Cross-Income Exposure Relate to Friendship Formation?

Having documented the rate of exposure to upper-income students, a question that follows is if exposure to upper-income students (as captured in this paper) matters for lower-income students' long-term outcomes. One way to answer this question is to identify if the measure of exposure to upper-income students relates to another measure that has already been documented to strongly correlate with economic mobility—Chetty et al. (2022) cross-income friendships measure.

To identify how a school's cross-income exposure relates to its students' average likelihood of cross-income friendship, I link the Texas administrative data with public high school measures on "economic connectedness" captured by Chetty et al., (2022). Economic connectedness is defined by Chetty et al. (2022) as the proportion of high-SES friends among low-SES individuals on Facebook divided by the share of high-SES individuals in the population. For each high school, I create a measure of exposure with which I capture the average proportion of lower-income students' classmates that are upper income in 2012.[28]

The likelihood that a lower-income student is exposed to a upper-income classmate is highly predictive of a school's economic connectedness, as shown in Figure 5 Panel (a). The correlation

26. The gap in cross-test score exposure is smaller than cross-income exposure as shown in Figure A7. Lower-achieving students are those who scored in the bottom 29 percentiles of their grade 4 reading test.

27. One test score may be subject to larger measurement error compared to the income measure which is based on multiple years of Free/Reduced Lunch status. I find similar patterns if I define achievement by students' average grades 3 to 8 test scores as shown in Figure A8.

28. I use students enrolled in high school in 2012 instead of 2019 because the friendship measures are based on Facebook friendship networks for individuals 25–44 as of 2022. I was able to merge 1,132 schools in the Texas data with the high school friendship measures, that is, 51% of schools serving grades 9–12. Of the 1,132 schools, 981 have data on economic connectedness measures.

between the average proportion of upper-income classmates among lower-income students (exposure) in a school and economic connectedness is between 0.86 and 0.93.[29] The strong correlation between my measure of exposure to upper-income students and the rate of cross-income friendships (economic connectedness) as captured by Chetty et al. (2022) can be thought of as a validity check: both measures seem to be capturing the rate of cross-income interactions in a school.

Conditional on a school's income composition, students in some schools have a lower likelihood of befriending higher-income students (higher friending bias) (Chetty et al., 2022).[30] It is not clear why that is. It could be that lower-income students are exposed to the same proportion of upper-income students in both schools, but teachers or student characteristics better enable cross-income friendships in one school and not the other. Alternatively, schools' friending bias may capture differences between schools in within-school sorting by income, i.e., conditional on a schools' income composition, lower-income students may be more likely to share a classroom with an upper-income student in one school than in another school. I find that the correlation between within-school sorting by income (as captured by the variance ratio) and friending bias is between 0.61 and 0.67 as shown in Figure 5 Panel (b).[31] The high correlation between school classroom sorting by income and friending bias suggests that the friending bias measure is likely capturing differences in lower-income students' classroom exposure to upper-income students, conditional on school income composition.

Cross-income exposure and friendship formation as measured by Chetty et al. (2022) are strongly correlated at the school level. That said, it is not clear how predictive exposure to upper-income students is of individual students' likelihood of forming (close) friendships with upper-income students. Using student-level data from Add Health on close friendships (top five friends), I similarly find that a student's school and extracurricular composition (i.e., cross-income exposure) strongly predicts the composition of their close friendships–though to a lesser extent–with correlations of 0.37 and 0.40, respectively. The relationship between exposure to high-SES students and friendship formation is presented in Figure A17.[32] Refer to Supplementary Appendix C for more details

29. The range is based on whether I use the economic connectedness measure based on students' own income or students' parental income.

30. Friending bias is calculated as one minus the share of friends who are high SES divided by the share of individuals in the group who have high SES. Refer to Chetty et al. (2022) for more details.

31. Refer to Supplementary Appendix B for more details on the variance ratio measure.

32. The fitted line is below the 45 degree line, suggesting that the composition of the school and extracurriculars does not perfectly predict the average difference in the proportion of high-SES peers (it is not 1-to-1) for low-SES students, but it comes

on how SES is defined using the Add Health data and how the relationship between school and extracurricular composition and friendship network is calculated.

6 Cross-Income in Schools and Lower-Income Students' College Enrollment, Graduation and Employment?

6.1 Sample

Up to this point the goal was to understand how likely cross-income exposure in schools is and how it relates friendship formation. In this section, I examine if and why the share of upper-income classmates in a school matters for lower-income students' college enrollment and employment outcomes.

In the prior section the goal was to understand students' schooling experience as it relates to their share of upper-income classmates. In order to understand their schooling experience, I followed three cohorts of students, starting with the earliest cohort we can observe classroom data for–the 2012 cohort–to the last cohort we can follow from grade 5 up to expected grade 12 (i.e., up to 2019, before COVID)–the 2014 cohort.

In this section, to improve precision given the small variation year-to-year in the share of upper-income students in a school, I need to follow a large number of cohorts in a school into adulthood, therefore the sample in this section is different. I identify ten cohorts of grade 9 students starting in 2010. Students are grouped into cohorts based on the year they are enrolled in grade 9. For example, students enrolled in grade 9 in 2009–2010 are grouped into the 2010 cohort.[33] I observe ten cohorts of students (2010 to 2019) for the college enrollment and secondary school outcomes. For the college graduation and wages in early adulthood outcomes, I follow five cohorts of students (2010 to 2014), to allow for enough time for students to graduate college and find employment at expected age 22-28.

close: For low-SES students, the slope between school composition and the proportion of high-SES friends is 0.78, and the slope between extracurriculars and the proportion of high-SES friends is 0.71.

33. The income measure is based on the number of years on free/reduced price lunch. I observe each cohort for 10 years. For example, students in the 2010 cohort who never had free/reduced lunch between 2004 and 2013 are identified as higher income. The data are at the student-school level. Students are assigned to their grade 9 school. Some students are enrolled in multiple schools in grade 9.

6.2 Identification Strategy

Descriptively, I find that students independent of grade 8 reading (baseline) test-scores appear to perform better when in classrooms with more upper-income classmates during their high school years, as shown in Figure A18.The positive relationship between a student's proportion of upper-income classmates and long-term outcomes may be driven by differences in access to school resources correlated with the proportion of upper-income classmates.

One way the peer effects literature has gone around identifying if the relationship between peer composition and individual student outcomes is capturing differences in access to school resources (or selection) or peer effects is by using (small) changes in cohort composition between adjacent cohorts in the same school. These marginal, temporary, changes in cohort composition are less likely to change students' access to school resources and to be predicted by parents choosing to enroll their kids in a school. The assumption is that adjacent cohorts of students who attend the same school would have a similar school environment and the only difference between them is that some happen to have a slightly different cohort composition (e.g., more upper-income students) due to random draws from the school population that are unrelated to changes in school characteristics. Using cross-cohort deviations in peer composition to capture peer effects dates back to Hoxby (2001) and since then has been used extensively in the peer effects literature.[34]

Building on Hoxby (2001), I use within-school between-cohort deviations in the share of upper-income peers to capture the impact of having more upper-income peers on lower-income students' outcomes. Note that in this section (unlike in prior sections) I use variation in grade 9 school cohort composition regardless of whether those students end up in the same classroom.[35] My preferred specification is shown in Equation (1):

$$Y_{isc} = \beta_0 + \beta_1 PropHighIncome_{-isc} + X'_{isc}\beta_2 + \delta_c + \delta_s + c \times \delta_s + \epsilon_{isc} \tag{1}$$

where $PropHighIncome_{-isc}$ is the share of student i's peers (excluding herself) in cohort c that are upper income; β_1 captures the impact of an unexpected change (residual of the linear school

34. For examples see Feld and Zölitz (2017), Lavy and Schlosser (2011) and Angrist and Lang (2004).

35. I use variation in school-cohort instead of classroom-cohort because I cannot track the same classrooms over time and students self select into classrooms.

trend) in the composition of peers on the long-term outcome; and X'_{isc} is a vector of student i's characteristics (gender, race/ethnicity and math and reading grade 8 test scores). δ_s captures a school fixed effect to account for level school differences in student outcomes, and $c \times \delta_s$ captures school-specific time trends (c is a linear cohort trend). I also include cohort fixed effects, δ_c, to capture any cohort-specific changes in the sample. Because the treatment is at the school-cohort level, I cluster the standard errors at the school level. I run the regression only for lower-income students since I am interested in how exposure to upper-income peers impacts lower-income students' long-term outcomes.

Using Equation (1), a standard deviation in the residual from school trend proportion of upper-income students is 2 percentage points.[36] At the 1st percentile are cohorts with 5.9 percentage points fewer upper-income students, and at the 99th percentile are cohorts with 6.2 percentage points more upper-income students. Table 2 summarizes the residual variation in the composition of the cohort and Figure A21 presents the distribution of the residual variation in cohort composition. The median lower-income student is in a school-cohort with 578 students, 8% of whom are upper-income. As such, a 2 percentage point change in proportion of upper-income students for the median student is an increase in the number of upper-income students in their cohort from 46 to 58—that is from 1.4 to 1.7 upper-income students in a (median) class of 17 students.[37]

These temporary (small) shocks to cohort composition are unlikely to change the resources students have access to (e.g., teacher quality, AP courses offered, and school budgets). They also likely would not change classroom norms, which is a potential mechanism through which exposure to upper-income peers may impact long-term outcomes. These small changes may impact lower-income students through direct interactions like the passage of institutional knowledge or changes of expectations on what colleges may be feasible. It could also be through changes in teacher behavior or expectations in response to small changes in classroom income composition.[38]

36. The residual standard deviation is similar to the median standard deviation expected from random draws from the school population as shown in Figure 6

37. A student's cohort composition may not be representative of their actual exposure to upper-income students. I find that a 10-percentage-point increase in the proportion of upper-income peers in one's cohort increases lower-income students' proportion of upper-income classmates by 5.9 percentage points as shown in Table A8. The diluted impact of peer cohort composition on lower-income students' classroom exposure to upper-income peers may be in part due to within-school sorting by income. I find that a 10-percentage-point increase in the proportion of upper-income students in a cohort increased the level of within-school income sorting between classrooms by 1.4 percentage points, as shown in Table 7.

38. Using this research design I am not able to identify why having more upper-income peers may have spillovers on lower-income students, but I can provide suggestive evidence on potential mechanisms like peer achievement and changes in access to (observable) school resources.

The key identifying assumption is that cohort deviations from school trend in the share of upper-income students are essentially random—they are uncorrelated with unobserved cohort changes that may be driving lower-income students' outcomes. For example, there may be random fluctuations in the proportion of upper-income students between cohorts attending the same school because a town doctor (upper-income family) happens to have two children of age groups that match certain cohorts and not others. The assumption that the fluctuations in the share of upper-income students are random is violated if, for example, a school offers more AP courses and in response more upper-income students enroll in the school. To address the school time-varying selection concern I include school-time trends in Equation (1), similar to Hoxby (2001). The school time trends capture systematic linear changes in cohort composition that may be driven by school and student unobserved changes. The source of variation that remains when including school trends is "unexpected shocks" (temporary) deviations from the school time trend in the share of upper-income peers.

I use a Monte Carlo Simulation to assess whether the observed within school deviations from school trend in the proportion of upper-income students look like the variation that would result from random draws of upper-income students from the school population. For each school, I randomly generate the income of the students in each cohort using a binomial distribution function with p equal to the average proportion of upper-income students in the school across all years, then compute the within school standard deviation of the residuals and repeat this process 1,000 times to obtain the empirical percent confidence interval for the standard deviations.[39] As shown in Figure 6 the distribution of schools' average simulated standard deviation from school mean is similar to the observed schools' standard deviation in the proportion of upper-income students from school trend.[40] I find that 92 percent of the schools had a standard deviation within the empirical 95 percent confidence interval of the school's distribution of simulated standard deviations, which is close to what we would expect from random draws of the school population.

School trends may not capture the pattern of school time-varying changes well. As an additional robustness check, in Tables 3 and 4 Models (5) and (6), I present falsification tests based on

39. This method is based on Lavy and Schlosser (2011) simulation of deviations from school mean proportion female students.

40. The right tale of the observed distribution of standard deviations is longer than the simulated distribution. This is likely in part because the simulated distribution is based on the average from multiple simulations. I re-estimate the main estimates restricting the sample to schools where the standard deviations is within its 95 percent confidence interval and the estimates remain consistent as shown in Table A20.

placebo cohort proportion upper-income peers replacing the true cohort composition with the cohort composition in the younger ($t-1$) or older cohort ($t+1$).[41] I show that adjacent cohorts' peer income composition do not appear to impact a students' own outcomes suggesting I am not capturing spurious correlations between the proportion of upper-income peers and time-varying school factors. The generally small null effects on adjacent cohorts also suggests that there are no (detectable) spillovers between adjacent cohorts—the impact seems to be driven by students' own cohort peer composition.[42]

We might be concerned that changes in the proportion of upper-income students are capturing other simultaneous changes in lower-income students' characteristics that are correlated with their college enrollment and wages (common shocks). For example, lower-income students in cohorts with larger deviations from school trend in the share of upper-income students may happen to have higher family income which is driving their higher college enrollment. To assess the possibility of common shocks, I check whether lower-income students' demographic characteristics are correlated with deviations from school trend in the share of upper-income students. The share of upper-income students does not seem to correlate with lower-income students' baseline characteristics (gender, race and immigrant status) suggesting that the estimates are not driven by simultaneous changes in lower-income students' characteristics as shown in Table A7. Lower-income students' parental income reported on financial aid data also appears to be no different when exposed to more upper-income peers, suggesting that the estimates are not driven by cohort specific changes in lower-income students' household income that correlate with better long-term outcomes.[43]

One question we might have is how much overlap there is between the share of upper-income students a student has in grade 9 and that in earlier grades. The treatment—deviations from high school trends in the proportion of upper-income students—might be capturing changes in the cohort's share of upper-income peers that date back to earlier school years.[44] My main specification controls for students' own grade 8 reading and math test-score and so in so far as students' grade

41. The falsification test is used by Lavy and Schlosser (2011) to identify if the impact of female peers is driven by time-varying school changes.

42. The only exception is four-year college enrollment for the falsification test at $t-1$, but it is not consistent with the wage estimates and may be spurious.

43. Note that the financial aid data is based on a select group of students and the proportion of lower-income students applying for financial aid slightly increases–by 0.5 percentage points for every 10 pp increase in the share of upper-income students–when lower-income students are exposed to more upper-income peers.

44. I find that a 10 p.p. increase in the proportion of upper-income students in high-school is associated with a 6 p.p. higher share of upper-income students in grade 8.

8 test-scores are capturing the impact of prior exposure to upper-income students, the remaining impact of exposure to upper-income students is capturing the impact of high-school exposure. I also present estimates including fixed effects for students' grade 8 school-cohort to capture the impact of exposure to upper-income students in high school independent of middle school exposure and to address the concern that grade 8 test-score may be a function of grade 8 exposure to upper-income peers.[45] By including grade 8 school-cohort fixed effects I limit the variation to students who attended the same grade 8 school and cohort but happen to attend high schools with differing deviations from school trend in the proportion of upper-income students. The coefficients on the proportion of upper-income peers are generally consistent but less precise when controlling for grade 8 school-cohort as shown in Table A23 Model (5). The consistent estimates suggest that most of the impact captured in the main specification is driven by differences in high school exposure to upper-income peers, rather than earlier school years.

We may be interested in the cumulative impact of deviations from school trends in the proportion of upper-income students on lower-income students. As such, I also present results without controlling for grade 8 test-scores as shown in Table A23 Model (3)–the estimates are consistent, but slightly larger.[46]

6.3 Main Results

I find evidence consistent with the notion that a lower-income student in a cohort with a higher share of upper-income peers is more likely to enroll in college and earn higher wages. I find that lower-income students are more likely to enroll in college (both 2-year and 4-year) when exposed to more upper-income peers, as shown in Table 3. The results are based on Equation (1). The coefficient on the change in the share of upper-income peers is 0.049 in Model (3) for lower-income students' 4-year college enrollment, implying that lower-income students' likelihood of enrolling in 4-year public colleges rises by 0.49 percentage points ($p = 0.002$)for every 10-percentage-point

45. Ideally, to disentangle the role of peer achievement, I would want to control for student achievement measured before students enroll in school or to instrument for later achievement, but in the absence of this I use grade 3 test-scores which are the earliest test-scores I have for students. Table A13 Model (4) shows that the coefficients on the impact of the proportion of upper-income peers is consistent independent of if I control for grade 3 or grade 8 student peer reading test-scores.

46. Another concern is selective attrition between earlier school years and high school. Switching between school districts in Texas is not common: 90% of students in grade 8 remain in the same school district by grade 9 and 97% are still enrolled in Texas public (or charter) schools the following year. In addition, as discussed earlier, lower-income students in cohorts with a higher share of upper-income peers in grade 9 appear no different on a number of demographic characteristics as shown in Table A7 suggesting that selective attrition is unlikely.

change in the share of their class that is upper income. A 10 percentage point change is equivalent to moving from the 1st to 99th percentile in the schools' share of upper-income students.[47] I do not find strong evidence of an impact on a student's likelihood of graduating from college and enrolling in a selective college.[48]

I also find evidence of a positive impact on average wages and income percentile rank.[49] The average wage of lower-income students by 2023 (by age 22–28) increased by 434 dollars (2.1%) ($p = 0.01$) as shown in Table 4 Model (3), and their percentile rank (within cohort) increased by 0.36 percentiles ($p = 0.03$) for every 10-percentage-point change in the share of upper-income students.[50]

The positive impact of exposure to upper-income students on wages likely does not operate exclusively through improved college enrollment. Zimmerman (2014) finds that the marginal admission to a public university in Florida for a student on free/reduced lunch increases their 4-year college enrollment by 14 percentage points and quarterly wages by $950.[51] This suggests that an increase in 4-year college enrollment of about 0.5 percentage points would increase yearly earning by $133. The increase in average earning I observe is around three times that at $434, suggesting that the impact on wages likely does not operate only through the impact on lower-income students' 4-year college enrollment.

Having an upper-income student might matter for a lower-income student independent of if the upper-income student is academically high- or low-achieving. Exposure to upper-income peers is highly correlated with exposure to higher-performing peers (correlation of 0.66 among lower-income students). As such, we may be capturing the impact of exposure to high-achieving students, regardless of family income. To disentangle the two, I run another regression that controls for peer achievement. In-line with Section 4.3, high-achieving students are defined as those who performed in the top quarter of their grade 8 reading test score so that it is equivalent to the share of upper-income students. If peer income impacts college enrollment only through peer test scores, the

47. The relationship between the residual share of upper-income students and college enrollment and wages appears to be linear as shown in Figures A22.

48. The estimates are consistent when controlling for changes in cohort racial/ethnic composition, as shown in Table A14, suggesting that the impact of exposure to upper-income peers is independent of changes in peer racial/ethnic composition.

49. Income percentile rank is based on ranking the full sample of students in a given cohort based on their wage in 2023. Students who do not have wage data are assumed to earn 0 that year.

50. The estimate is based on imputing students who are missing unemployment insurance data with 0. If instead I only run the regression on students with employment data (61% of lower-income students) the wage gain is $545 for a 10 p.p. increase in the share of upper-income students—a 1.6% increase from the control mean for students with employment data of $33,743. The share of upper-income students does not seem to impact students' likelihood of being in the unemployment insurance data.

51. Adjusted for inflation, assuming the $737 wage gain reported in Zimmerman (2014) is based on 2014.

coefficient on the proportion of upper-income students would approach zero when I control for peer test scores.

I find that the impact of exposure to upper-income peers on college enrollment remains positive and consistent with previous estimates when controlling for peer test score as shown in Tables 4 and 3, Model (4)—if anything, it appears to be slightly larger. The consistent, slightly larger, estimates on the proportion of upper-income students suggest that there is something about being exposed to upper-income peers that impacts student college enrollment and wages through mechanisms other than peer achievement (orthogonal to peer test scores). The patterns are consistent independent of how higher-achieving students are defined: using math (instead of reading) grade 8 test scores, average math and reading, grade 3 and/or average grades 3 to 8 test-scores as well as a continuous measure of peer achievement as shown in Table A13.[52]

The positive impact on college enrollment and wages of exposure to upper-income students appears to be driven by exposure to lower-achieving upper-income students as shown in Table 6 where I split peers into four categories based on income and achievement. A 10 percentage point increase in the share of upper-income, higher-achieving students has no detectable impact on lower-income students' four year college enrollment (-0.2 percentage points, $p = 0.25$) and wages (\$155, $p = 0.48$) compared to a 1.2 percentage point (8.6%) ($p < 0.001$) increase in four year college enrollment and a \$479 increase in wages (2.3%) ($p = 0.016$) when exposed to 10 percentage points more upper-income, lower-achieving, students. Lower-achieving students are defined as those who scored below the top quartile of the grade 8 reading test.[53]

To assess whether similarity in achievement matters for these effects, I re-estimate the models from Table 6, this time categorizing upper-income peers by their test-score proximity to lower-income students. Specifically, I identify three subgroups of upper-income peers: (1) those scoring in the same quartile of grade 8 reading scores as the focal student, (2) those scoring one quartile above or below, and (3) those scoring two quartiles apart. Figure 7 summarizes the estimated

52. Ideally, to disentangle the role of peer achievement, I would want to control for student achievement measured before students enroll in school or to instrument for later achievement, but in the absence of this I use grade 3 test-scores which are the earliest test-scores I have for students.

53. This is consistent with the notion that peer achievement might have a negative impact on lower-income students. In Tables A11 and A12 I present a horse-race between the impact of the proportion upper-income and the proportion high-achieving students in a cohort. The impact of exposure to high-achieving students appears to be negative. Feld and Zölitz (2017) similarly find using random assignment to sections at university that peer academic achievement may negatively impact lower-achieving students.

coefficients, revealing that the positive impacts on both four-year college enrollment and wages are concentrated among upper-income peers with similar test scores.[54]

The relationship between the share of upper-income peers and long-term outcomes may operate through improved high school test scores and behavioral outcomes (discipline and attendance). I find that a 10-percentage-point increase in the share of upper-income peers increases lower-income students' average reading test score by 0.02 standard deviations.[55] A 10 percentage point increase in the share of upper-income students also appears to decrease students' out-of-school and in-school suspension by about 0.34 and 0.55 percentage points, respectively, as shown in Table 5 Model (3). I find a small and insignificant impact on students' attendance.

I find some evidence suggesting that exposure to upper-income students may be stronger within racial/ethnic groups, but ultimately most estimates are noisy, as shown in Tables A15 to A17. The impact on wages appears to be considerably stronger for White students exposed to more upper-income White students (a 10 p.p. change increases wages and income rank in 2023 by 1,114 dollars and 1.5 percentile ranks). The impact on four-year college enrollment is also considerably larger for Black students exposed to more upper-income Black students (a 10 p.p. change increases four-year college enrollment by 4.9 percentage points).

6.4 Addressing Economic Segregation and the Role of Access to School Resources

The positive impact of temporary small changes within a school in the share of upper-income students on lower-income students' outcomes suggests that the gains to improving cross-income exposure likely do not operate exclusively through changes in access to school resources. I examine whether lower-income students' access to experienced teachers and per pupil spending shifts with peer-income composition and find no detectable effects on teacher experience or per-pupil spending; the coefficients are small and statistically indistinguishable from zero (Table 7).

That said, lower-income students are slightly less likely to enroll in Advanced Placement (AP)

54. Additional analysis in Appendix Figure A23 suggests the positive effect of exposure to upper-income students by proximity is mainly driven by lower-income students in the bottom quartile of the grade 8 score distribution, benefiting most from a higher share of similarly low-achieving but higher-income peers.

55. The impact on test scores may be driven by a change in the composition of students taking the test. I do not find evidence that the change in peer income composition impacted the share of students missing reading test scores in high school.

courses when the cohort includes more upper-income peers. A 10 percentage point increase in the share of upper-income students is associated with 0.06 fewer AP courses taken by lower-income students, on average. The decline in the number of AP courses taken by lower-income students is not explained by any changes in the number of advanced courses offered in a school; schools seem to offer a similar number of AP courses independent of the share of upper-income students (Table A10). I find that within-school sorting by income rises by 1.4 percentage points for every 10 percentage point increase in the share of upper-income students in a cohort suggesting that while peer-composition changes may leave average school resources unchanged, they can alter which students access those resources.

Despite increased sorting and slightly lower AP enrollment, lower-income students still benefit from exposure to more upper-income peers, on average, suggesting mechanisms beyond access to observable school resources.[56] To address the gap in exposure to upper-income peers documented in Section 4 we would want to swap upper- and lower-income students to improve lower-income students' exposure to upper-income peers. Since there are three income groups (upper-, middle- and lower-income) I control for the proportion of middle-income students to try and simulate an experiment where upper- and lower-income students move around but middle-income students stay since their average exposure to upper-income peers is close to the integration benchmark.

I find evidence suggesting that improving cross-income exposure (i.e., swapping upper- and lower-income students) could be a win-win/neutral effect on lower- and upper-income students with respect to wages in early adulthood. A 10 p.p. increase in the share of upper-income students (holding constant the share of middle-income students, i.e. swapping lower-income students with upper-income students) raises lower-income students' wages in early adulthood by 2.7% ($p = 0.002$; Table A18). Conversely, a 10 percentage point increase in the share of lower-income students (again holding the middle-income share fixed) has no statistically detectable effect on upper-income students' wages; the point estimate is -0.9% ($p = 0.30$; Table 8)—negative but small in magnitude.[57] Under a 10–percentage-point swap counterfactual, the estimated slope implies a 6% reduction in the upper–lower income gap in quarterly wages in early adulthood.

56. Upper-income peers may affect access to unobserved resources (e.g., parent volunteering for school events or elective courses). However, since policies can only impact access to school resources observed in the data, unobserved changes in access to school resources would likely require addressing school socioeconomic segregation.

57. There is some suggestive evidence of a negative effect on upper-income students' graduation likelihood, but it does not translate into lower wages in early adulthood. Given the larger standard error, I can rule out wage declines greater than 3.6%.

Note that the estimates are based on temporary shocks in exposure to upper-income peers within the same school. As such, it captures the impact on lower- and upper-income students who remain in the same school, but not the impact on upper- and lower-income students who would have to move schools to improve cross-income exposure. It also captures the impact of temporary changes which may be a lower-bound on potential gains from long-term changes in the proportion of upper-income peers on lower-income students if long-term changes are more likely to improve access to school resources.

To bound the potential wage gains from exposure to upper-income students, I use larger differences in the share of upper-income students between schools. The variation in exposure to upper-income students between schools is more prone to bias; lower income students attending schools with a higher share of upper-income peers are more likely to be systematically different. Nevertheless, it can give us a sense of the potential gain from larger variations in the proportion of upper-income students over a longer period of time. In Table A19 Model (1) I control for student test scores and demographic characteristics, but only include cohort fixed effects. In Model (2) I include middle school-cohort fixed effects and in Model (3) I include district fixed effects. In Model (2) I use variation in the proportion of upper-income students in high school between students who attended the same middle-school cohort, and in Model (3) I use variation among students in the same district who happen to be in different cohorts or high schools that had a different proportion of upper-income students.[58] The average wage gain in Table A19 ranges from \$413 to \$518 for a 10 percentage-point increase in the proportion of upper-income students in a students' grade 9 school cohort. This is similar to the gain of \$434 from my main specification using only within school differences in the share of upper-income students. The similar estimated wage gain compared to the main specification suggests that the estimate from the main specification is likely representative of the potential longer-term gain from larger increases in exposure to upper-income students. In Section 6.6 below I show that the estimated impact is similar to that expected from Chetty et al. (2022) movers design estimates.

58. A standard deviation in the residual variation in the proportion of upper-income students ranges between 15 and 8 percentage points more upper-income students in Table A19, Models (1)-(3).

6.5 Robustness Checks: Treatment Definition and Measurement Error

The deviations in the proportion of upper-income students may be capturing small measurement errors in a students' income, i.e., lower-income students' peer income composition did not change it just happens to be that one student who should have been assigned one year on free/reduced lunch was not assigned to free/reduced lunch due to administrative or other errors. I find that a 10 p.p. increase in the share of upper-income students–defined as students never on free/reduced lunch–is associated with a 11 thousand dollars higher average cohort parental income as reported on financial aid applications and 8 p.p. fewer cohort average proportion of years on free/reduced price lunch status as shown in Table A22. This suggests that differences within a school between cohorts in the share of upper-income peers, as defined in this paper, is capturing real differences between cohorts in peers' parental income.

Students' likelihood of being on free/reduced lunch in high school may be correlated with the share of upper-income students in the cohort. For example, lower-income students may be less likely to enroll in free/reduced lunch when in a cohort with a higher share of upper-income students. If so, then we may be capturing differences in selection into free/reduced lunch that are correlated with the share of upper-income students. To address this concern, I re-estimate the regression using a definition of lower- and upper-income students based on their free/reduced-price lunch status in the years prior to high school.[59] When only using prior to high school years to define income, I find a similarly positive impact on lower-income students' college enrollment as shown in Table A21. The impact on college enrollment remains consistent in size and precision, and the impact on wages is positive, but is smaller and no longer significant at the conventional level ($222 increase for a 10 p.p. change in the share of upper-income students). By only using prior to high school years we are missing (potentially) important information on students' degree of economic disadvantage (introducing attenuation bias), but it is likely less prone to the bias concerns discussed here.

59. Twenty-six percent of students who consistently receive free/reduced-price lunch prior to high school are no longer recorded as on free/reduced lunch in one or more high school years. This may reflect real improvements in household income—as parents may earn more as students grow older—or changes in the students' likelihood of applying for free/reduced lunch.

6.6 The Role of Friendship Formation

Assume that a student's exposure to upper-income peers has a causal impact on their income in adulthood (as suggested in the results of this paper). If the mechanism requires friendship formation, then the impact of exposure to upper-income students on wages would be smaller than the impact of befriending higher-income students on wages. If instead the impact of exposure to upper-income peers does not require friendship formation and is due to other factors related to exposure, then the impact of exposure to upper-income students may be larger than or equal to the impact of befriending higher-income students. Ideally, I would want to compare the causal relationship between friendship and wages to that between exposure and wages. To do so, I would need random variation in each of exposure and friendship. In the absence of this, I examine how the raw (no controls) relationship between friendship and wages compares to the relationship between exposure and wages in the Add Health data. In the Add Health data, I have information on students' reported income by age 24–32.

I find that the correlation between low-SES students' upper-income peers (exposure) and own income is slightly stronger than the correlation between students' proportion of high-SES friends and own income in early adulthood: correlation 0.07 relative to 0.03. The stronger correlation between exposure and students' income suggests that the relationship between peer composition and long-term outcomes may not require lower-income students to be close friends with upper-income students. Since the Add Health friendship data is based on listing students' top five friends, I cannot eliminate the possibility that the relationship between peer composition and long-term outcomes may require (weak) friendships with upper-income peers. That said, it suggests that information on a lower-income student's exposure to upper-income peers may be more predictive of a student's wage in adulthood than information on a students' proportion of close upper-income friends.

I can similarly compare the Chetty et al. (2022) measure of the relationship between economic connectedness and income in adulthood to the relationship between exposure to upper-income students and long-term outcomes captured in this paper. Using movers design, Chetty et al. (2022) find that moving to a neighborhood with 1 unit higher economic connectedness increases relative mean income rank in adulthood by 9.8 percentile points. The slope of the relationship suggests that a 10 percentage-point difference in a schools' proportion upper-income peers (equivalent to a 0.16 units difference in economic connectedness) would increase mean income rank in adulthood by 1.6 percentile points.[60] This estimate is based on the slope of the relationship between years of exposure and income percentile—it assumes 20 years of exposure (from birth). Assuming the relationship between years of exposure and income percentile is linear up to 20 years of age, then exposure in high school years (four years) would yield a 0.3 percentile rank increase in mean income rank in adulthood which is similar to the increase in mean income rank in this paper of 0.36 percentile ranks.[61]

The Add Health data comparison and the estimates from Chetty et al. (2022), together suggest that there may not be much additional gain from information on cross-income friendships relative to cross-income exposure alone for predicting lower-income students' long-term outcomes. In other words, it is not clear that the impact of exposure to upper-income students on long-term outcomes necessitates friendship formation.

7 Discussion and Conclusion

I present new evidence on the stark income-based disparities in students' classroom share of upper-income peers and evaluate its implications for lower-income students' college enrollment and wages. Using rich administrative data from Texas and a new way of measuring family income using repeated measures of free/reduced lunch, I show that lower-income students encounter far fewer upper-income classmates over their schooling years than their upper-income counter parts: cumulatively, the median lower-income student shares classrooms with fewer than 40 upper-income peers out of roughly 700 classmates between grades 5 and 12. Although the limited exposure to upper-income classmates is largely driven by residential and school-level segregation, classroom-level sorting—particularly in high school—accounts for a meaningful share and may be more amenable

60. The conversion from economic connectedness units to school proportion of upper-income students is based on the slope of the relationship between a schools' economic connectedness as captured by Chetty et al. (2022) and average lower-income students' proportion of upper-income classmates as captured in Section 5 in this paper.

61. To compare the estimates of the impact of economic connectedness to the estimates of the impact of exposure to upper-income peers in this paper, we need to assume that for a lower-income student, the effect of a 10-percentage-point change in the proportion of upper-income peers in the same school is equivalent to moving to a *neighborhood* with a 10-percentage-point difference in the proportion of upper-income peers. The 9.8-percentile points estimate can serve as a rough benchmark, but ultimately it is capturing differences between neighborhoods that could include differences in school quality and neighborhood institutions. In comparison, the estimates in this paper only capture differences between peers in the same school.

to policy intervention.

Using the residual from school trend variation in the share of upper income students across cohorts, I find that increased exposure to upper-income peers improves lower-income students' four-year college enrollment and early adult wages. I show that these gains seem to be driven by exposure to upper-income, lower-achieving, students. These residual shocks in the share of upper-income peers are not correlated with changes in lower-income students' demographic characteristics and do not seem to change schools' (observable) resources (e.g. number of advanced courses offered and share of experienced teachers). These patterns indicate the benefits of cross-income exposure likely operate through channels other than the conventional school-level resource inputs and peer achievement. While evidence points toward social capital mechanisms, in this paper I do not directly measure information flows and peer networks. That said, I show that measures of cross-income friendships in the Add Health data and Chetty et al. (2022) using Facebook data strongly align with administrative measures of the share of upper-income peers.

At the same time, I show that a higher share of upper-income students within a cohort is associated with more within-school sorting by income and a reduction in AP course-taking among lower-income students. Average school resources do not change, but the allocation of opportunities across classrooms appears to respond to cohort composition. These findings underscore an important design lesson: policies that increase cross-income exposure may need to be paired with guardrails that protect equitable access to advanced coursework and limit tracking that could offset some benefits.

Taken together, the findings highlight an often-overlooked dimension of educational inequality: the independent value of cross-income exposure, beyond observable school-level allocation of resources and peer achievement. One concern in policy debates is whether reducing income segregation imposes costs on upper-income students. I find no evidence that increased exposure to lower-income peers reduces upper-income students' wages in early adulthood. The absence of detectable downside on upper-income students' wages suggests that reducing income segregation can generate mobility gains for lower-income students with minimal trade-offs for their upper-income peers. Moreover, prior work indicates that cross-class exposure can foster prosocial attitudes among advantaged students—such as greater generosity and support for redistribution (Rao, 2019; Ethan, Jorge, and Cody, 2025)—benefits not captured in my wage outcomes but consistent with broader social returns to integration.

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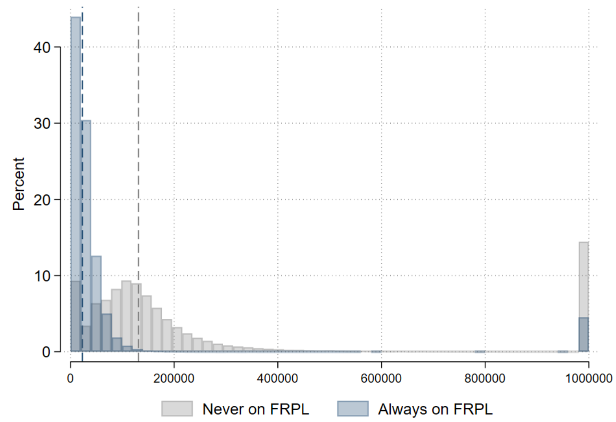
8 Main Tables and Figures

Table 1: Texas State Public School Student Demographics: Cohorts 2012-2014

Variable	Mean
Asian-American	.048
	(.213)
Black Students	.141
	(.348)
White Students	.320
	(.466)
Hispanic Students	.516
	(.500)
Enrolled in Title 1 School	.572
	(.495)
Free/Reduced Lunch Status	.608
	(.488)
Special Education	.094
	(.292)
Gifted Program	.106
	(.307)
English Language Learner	.262
	(.440)
Number of Students	1128554

This table summarizes demographic characteristics of the three cohorts of students I follow from grade 5 to expected grade 12. The demographic characteristics are based on student demographics (including free/reduced lunch status in fifth grade). The average is weighted by number of students across three cohorts. A cohort is defined by the year I observe them enrolled in grade 5 (2012, 2013 or 2014). The number in the brackets is the standard deviation.

Figure 1: Distribution of Parental Income by Free/Reduced Lunch Status



Notes: The sample includes students students enrolled in grade 5 in Texas between 2012 and 2014 who applied for financial aid during expected college enrollment years (2017—2022). Parental Income is based on the adjusted parental gross contribution listed on a student's financial aid applications at a single point in time. The vertical lines are the median income for each group. Outlier students with parents who have listed an income above 999,999 are top-coded to 999,999 (in earlier years, parents could not report income above 999,999 due to limited character space). Financial aid data are not available for 66%, 59% and 49% of students always, sometimes, and never on free/reduced lunch, respectively.

Table 2: Variation of interest: Between Cohorts 2010 and 2019–Residual Change in Income and Achievement of 9th Graders

Statistic	High-Income (1)	High-Achieve (2)
Standard Deviation	.021	.039
1st Percentile	-.059	-.115
5th Percentile	-.029	-.058
10th Percentile	-.019	-.039
90th Percentile	.019	.04
95th Percentile	.03	.057
99th Percentile	.062	.104

This table summarizes the residual variation in the proportion of high-income students and the proportion of high-achieving students. High-achieving students are those who scored in the top quarter of their grade 8 reading test. The residual variation is based on Equation (1): it is the residual variation after including cohort and school-trend controls. It is based on the sample of low-income students, i.e., it is weighted by the number of low-income students enrolled, which is the population of interest here.

Table 3: Impact of Proportion Upper-Income Students on College Enrollment for Lower-Income Students

	Main effects				Falsification test	
					t+1	t-1
	(1)	(2)	(3)	(4)	(5)	(6)
Enrolled in College/University						
Proportion Upper-Income	0.0918	0.127	0.0555	0.0907	-0.00960	0.0241
	(0.0224)	(0.0226)	(0.0210)	(0.0210)	(0.0219)	(0.0206)
Group Mean	0.370					
Enrolled in a Public 2yr College						
Proportion Upper-Income	0.125	0.146	0.0460	0.0706	-0.0161	0.00725
	(0.0238)	(0.0239)	(0.0223)	(0.0228)	(0.0219)	(0.0219)
Group Mean	0.290					
Enrolled in a Public 4yr College						
Proportion Upper-Income	0.0340	0.0561	0.0491	0.0705	-0.00239	0.0425
	(0.0142)	(0.0139)	(0.0156)	(0.0155)	(0.0161)	(0.0162)
Group Mean	0.140					
Enrolled in a Selective University						
Proportion Upper-Income	0.00752	0.0131	0.00699	0.0125	0.00111	0.00423
	(0.00397)	(0.00412)	(0.00470)	(0.00482)	(0.00508)	(0.00534)
Group Mean	0.0200					
School time trend			X	X	X	X
Proportion High-Achieving Peers		X		X		
N	1501742	1501742	1501742	1501742	1324870	1348885
N Clusters	2358	2358	2358	2358	2235	2270

Standard errors are in parentheses and clustered at the school level. Coefficients are based on Equation (1). The sample includes lower-income students only. Models (1) and (2) do not include school time trends. College enrollment outcomes include cohorts 2010–2019. Models (2) and (4) include both the proportion of upper-income and higher-achieving peers in the cohort. Group Mean is the average for lower-income students in the sample. Models (5) and (6) are placebo tests using the proportion of upper-income students of cohort $t+1$ Model (5) or $t-1$ Model (6).

Table 4: Impact of Proportion Upper-Income Students on College Graduation and Wages for Lower-Income Students

	Main effects				Falsification test	
					t+1	t-1
	(1)	(2)	(3)	(4)	(5)	(6)
Graduated College/University						
Proportion Upper-Income	0.0541	0.0605	0.0249	0.0311	-0.00239	0.0115
	(0.0213)	(0.0211)	(0.0229)	(0.0229)	(0.0254)	(0.0297)
Group Mean	0.170					
Wage 2023						
Proportion Upper-Income	3190.6	3700.9	4337.8	5141.6	641.3	-2882.8
	(1409.3)	(1425.5)	(1670.4)	(1689.0)	(1797.5)	(1916.5)
Group Mean	20490.5					
Income Percentile 2023						
Proportion Upper-Income	1.879	3.020	3.560	4.412	0.576	-2.027
	(1.363)	(1.383)	(1.620)	(1.638)	(1.706)	(1.943)
Group Mean	46.75					
School time trend			X	X	X	X
Proportion High-Achieving Peers		X		X		
N	700245	700245	700245	700245	695382	560867
N Clusters	1992	1992	1992	1992	1967	1929

Standard errors are in parentheses and clustered at the school level. Coefficients are based on Equation (1). Models (1) and (2) do not include school time trends. Models (2) and (4) include both the proportion of upper-income and higher-achieving peers in the cohort. Group Mean is the average for lower-income students in the sample. College graduation and wages include cohorts 2010–2014. Models (5) and (6) are placebo tests using the proportion of upper-income students of cohort $t+1$ Model (5) or $t-1$ Model (6).

Table 5: Impact of Proportion Upper-Income Students on High School Academic and Behavioral Outcomes

	Model 1	Model 2	Model 3	Model 4
Reading/English I Test Score				
Proportion Upper-Income	0.454	0.587	0.211	0.376
	(0.0830)	(0.0856)	(0.0782)	(0.0795)
Group Mean	-0.260			
N	1401373			
Missing Reading/English I Test Score				
Proportion Upper-Income	-0.0109	0.00306	0.0213	0.0232
	(0.0151)	(0.0139)	(0.0172)	(0.0176)
Group Mean	0.0700			
N	1501742			
Proportion of Days Absent				
Proportion Upper-Income	-0.00532	0.000687	-0.00579	-0.00529
	(0.00803)	(0.00820)	(0.00542)	(0.00544)
Group Mean	0.0900			
N	1400123			
Any Out-of-School Suspension				
Proportion Upper-Income	-0.0108	-0.0138	-0.0338	-0.0414
	(0.0260)	(0.0262)	(0.0173)	(0.0173)
Group Mean	0.200			
N	1418407			
Any In-School Suspension				
Proportion Upper-Income	-0.0639	-0.0679	-0.0546	-0.0583
	(0.0424)	(0.0430)	(0.0257)	(0.0255)
Group Mean	0.340			
N	1418407			
School time trend			X	X
Proportion High-Achieving Peers		X		X

Standard errors are in parentheses and clustered at the school level. Coefficients are based on Equation (1). Group Mean is the average for lower-income students in the sample. All outcome regressions are based on the 2010–2019 cohorts. The test score outcome has fewer observations since 6% of students are missing their reading scores. Most students take the Reading/English I test in grade 9. For students who took the test in 2010 and 2011, their scores were based on the Reading TAKS test. For students who took the test after 2011, their scores were based on the English I STAAR test. All raw scores were standardized based on the distribution of students who took the test that year.

Table 6: Impact of Changes in Income and Achievement Composition on Lower-Income Students: 4 Groupings

	(1) Any College	(2) 2yr Public	(3) 4yr Public	(4) Selective	(5) Grad Any	(6) Wage 2023	(7) Income Percentile
Proportion Upper-Income and High-Achieve	-0.0542	-0.0226	-0.0237	-0.00775	0.0257	1554.6	0.0397
	(0.0285)	(0.0272)	(0.0208)	(0.00707)	(0.0311)	(2163.6)	(2.104)
Proportion Upper-Income and Lower-Achieve	0.181	0.143	0.124	0.0197	0.0302	4804.8	3.651
	(0.0255)	(0.0272)	(0.0180)	(0.00553)	(0.0274)	(1983.2)	(1.930)
Proportion Low-Income and High-Achieve	-0.0565	-0.0245	-0.0255	-0.0267	-0.0559	-7056.8	-8.215
	(0.0406)	(0.0431)	(0.0297)	(0.0102)	(0.0420)	(2307.9)	(2.240)
Proportion Low-Income and Lower-Achieve	0.0876	0.0806	0.0436	0.00776	0.0133	-1200.6	-2.304
	(0.0198)	(0.0201)	(0.0115)	(0.00322)	(0.0178)	(1127.7)	(1.133)
N Clusters	2358	2358	2358	2358	1992	1992	1992
N	1501742	1501742	1501742	1501742	700245	700245	700245

Standard errors are in parentheses and clustered at the school level. The coefficients are based on Equation (1) but instead of the main independent variable (proportion upper-income students), students are split into four groups based on if they are upper-income and/or higher-achieving (test score in the top quarter of grade 8 reading test). Models (1)–(4) include cohorts 2010–2019 and Models (5)–(7) include cohorts 2010–2014.

Table 7: Impact of an Increase in the Proportion of Upper-Income Students on Access to School Resources

	(1) Class Sorting	(2) Teacher Experience	(3) Novice Teachers	(4) Spending	(5) Advanced Courses Taken	(6) AP Courses Taken
Proportion Upper-Income	0.135	0.433	0.00101	1804.2	0.538	-0.640
	(0.0115)	(0.363)	(0.0210)	(2226.9)	(0.275)	(0.168)
Group Mean	0.088	10.548	0.285	10605.050	2.265	1.276
N Clusters	2145	2184	2184	1873	2358	2366
N	1300067	1219772	1219772	1161067	1501742	1501750

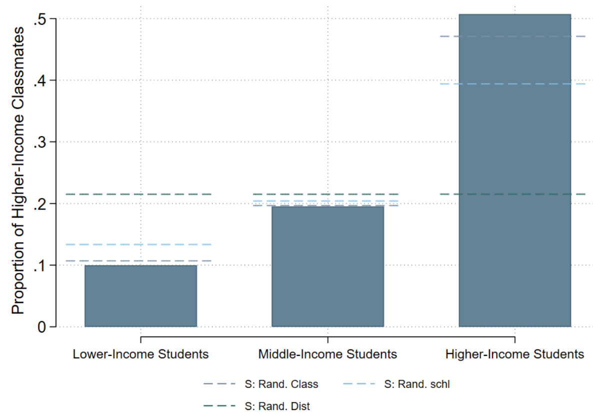
Standard errors are in parentheses and clustered at the school level. Coefficients are based on Equation (1). Model (1) includes cohorts 2011–2019 because the classroom data needed to calculate the within-school variance ratio are only available starting in 2011. Models (2)–(4) include cohorts 2012–2019 because teacher and school budget data linked to classrooms are only available starting in 2012. Spending is average school spending per pupil in a given year. Models (5)–(6) include cohorts 2010–2019 and capture the number of advanced and AP courses taken by a lower-income student, on average.

Table 8: Impact of Proportion Lower-Income Students, Holding Constant Mid-Income Students, on Upper-Income Students

	(1) Any College	(2) 2yr Public	(3) 4yr Public	(4) Selective	(5) Grad Any	(6) Wage 2023	(7) Income Percentile
Proportion Lower-Income	-0.0430	-0.0193	-0.0314	0.00610	-0.0808	-2970.7	-1.423
	(0.0286)	(0.0310)	(0.0278)	(0.0185)	(0.0414)	(3149.7)	(2.345)
Proportion Middle-Income	-0.0755	-0.0495	-0.0655	-0.00304	-0.102	-3564.9	-1.406
	(0.0231)	(0.0286)	(0.0228)	(0.0159)	(0.0333)	(2598.3)	(1.938)
Group Mean	0.680	0.490	0.420	0.160	0.470	33651.8	54.91
N Clusters	2129	2129	2129	2129	1818	1818	1818
N	1105943	1105943	1105943	1105943	549280	549280	549280

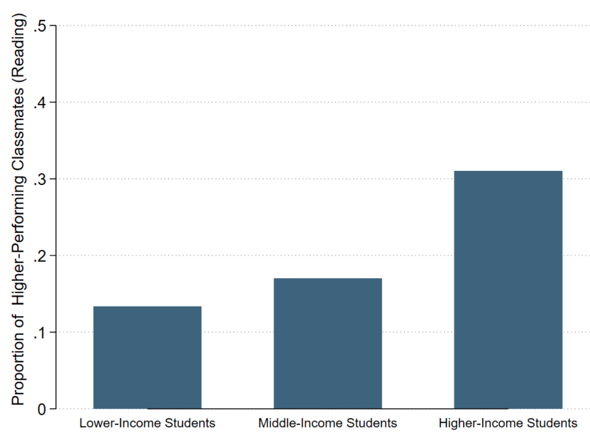
Standard errors are in parentheses and clustered at the school level. Coefficients are based on Equation (1) including a control for the share of middle income students in the cohort. The sample is limited to higher-income students. Models (1)–(4) include cohorts 2010–2019 and Models (5)–(7) include cohorts 2010–2014.

Figure 2: Exposure to Higher-Income Students: Observed Relative to Random Assignment



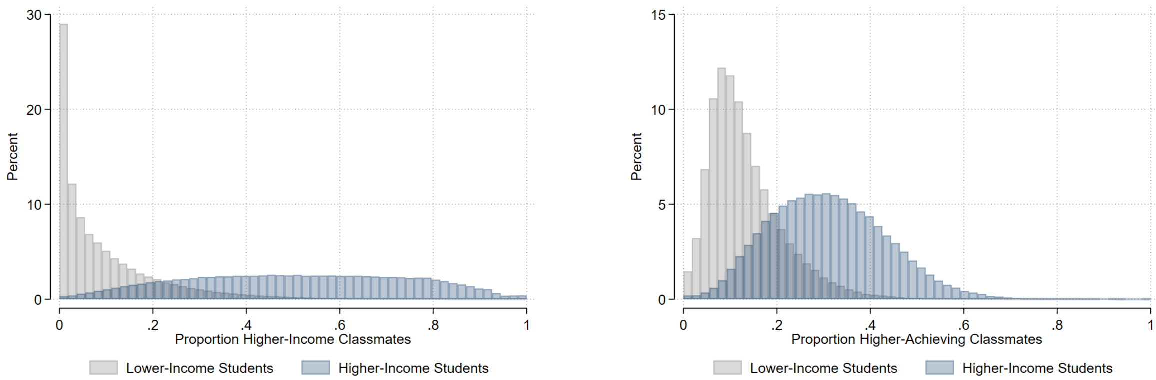
Notes: The bars capture the cumulative share of classmates that are upper-income calculated as the total number of upper-income students a student is in a classroom with from grade 5 to expected grade 12 (excluding own status) divided by the total number of students in each classroom (excluding self). The average exposure is weighted by the number of students in each group. The dashed horizontal lines present the various benchmarks for integration. "'S: Rand. Dist" lines capture the expected proportion of higher-income classmates had students been randomly assigned to districts: district integration benchmark. The "S: Rand. Schl" lines capture the expected proportion of higher-income classmates had students been randomly assigned to schools within a district (holding constant district composition): school integration benchmark. The "S: Rand. Class" lines capture the expected proportion of higher-income classmates had students been randomly assigned to classrooms within a school (holding constant school composition): classroom integration benchmark.

Figure 3: The gap in Exposure to Higher-Performing (Top quarter) Students is Smaller than the Gap in Exposure to Upper-Income Students



Notes: This plot captures students' cumulative proportion of higher-performing classmates between grade 5 to expected grade 12. I define higher-performing students as students who performed in the top 24 percentiles of test score based on the grade 4 standardized reading test. The percentiles are based on the distribution of students who have a grade 4 test score. Approximately 5% of students are missing grade 4 reading test scores.

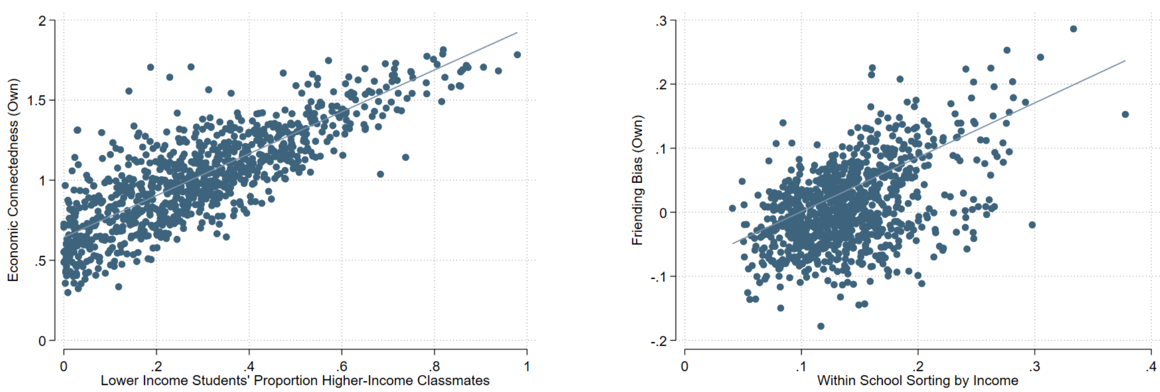
Figure 4: At the 25th Percentile, Lower-Income Students Have 1% Upper-Income and 7% Higher-Achieving Classmates



(a) Proportion of Upper-Income Classmates (b) Proportion of Higher-Achieving Classmates

Notes: Every time a student is in a classroom with an upper-income/higher-achieving student, this is counted as one interaction. Histograms present the distribution of the proportion of classmates in cohorts 2012–2014 who are upper-income/higher-achieving between G5-12 for higher- and lower-income students. The average number of classroom interactions between grades five and twelve is approximately 2000.

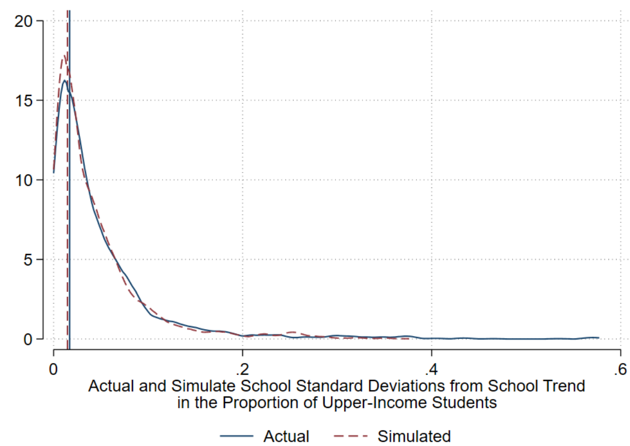
Figure 5: Strong Relationship between Likelihood of Befriending Higher-Income Students and Classroom Exposure



(a) Classroom Exposure and Economic Connectedness (b) Classroom Sorting by Income and Friending Bias

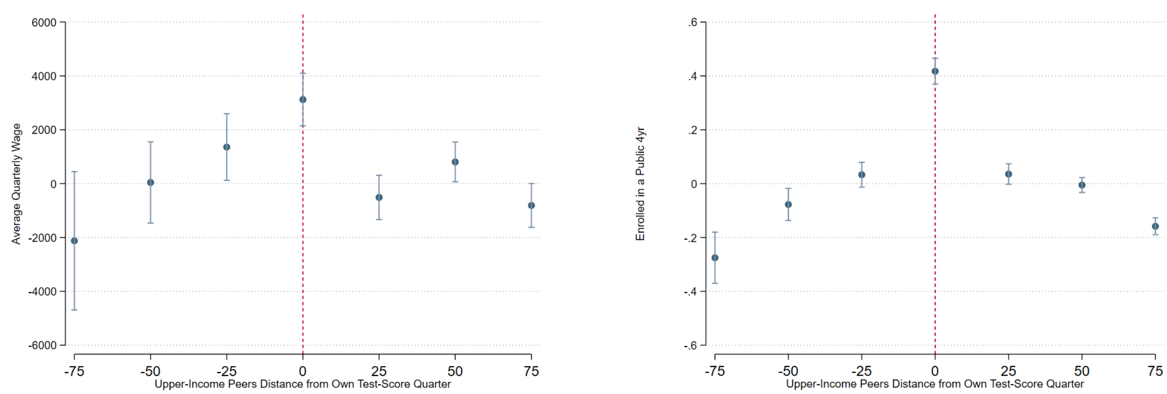
Notes: Each dot represents a school. Of the 1132 schools high schools linked the friendship formation high school measures in Chetty et al. (2022), 981 have data on economic connectedness. The fitted line weights schools by number of students enrolled. Panel (a) presents the correlation between high school measures of economic connectedness as captured by Chetty et al. (2022) and the proportion of higher-income students to whom lower-income students are exposed in each high school in 2012. Economic connectedness captures the likelihood of befriending a higher-income individual on Facebook. Panel (b) presents the correlation between high school measures of friending bias as captured by Chetty et al. (2022) and the difference in the proportion of higher-income students in higher- and lower-income students' classrooms, within a school (variance ratio). The variance ratio is based on 2012 student enrollment data. Friending bias captures the likelihood of befriending a higher-income individual on Facebook, conditional on the school proportion of higher-income students.

Figure 6: Simulated and Actual Distribution of within School Standard Deviations from School Trend



Notes: The figure captures the distribution of each school's standard deviation in the proportion of upper-income students from school trend (solid line) and each school's simulated average standard deviations in the proportion of upper-income students from school mean (dashed line). The vertical lines capture each distributions' median standard deviation in the proportion of upper-income students.

Figure 7: Impact of Having a Higher Share of Upper-Income Students by Proximity to Lower-Income Student's Own Test-Score



(a) Wage (2023)

(b) Four-Year College Enrollment

Notes: The figure captures the impact of having a higher share of upper-income students who (1) scored in the same quartile of grade 8 reading scores as the focal student (proximity= 0), (2) scored one quartile above (proximity= 25) or below (proximity= -25), (3) scored two quartile above (proximity= 50) or below (proximity= -50), and (4) scored three quartiles above (proximity= 75) or below (proximity= -75). Coefficients are derived from a regression analogous to that in Table 6, with the share of upper- and lower-income peers decomposed by test-score proximity. The model controls for the student's own grade 8 reading test-score quartile. In Figure A23 in the appendix, I estimate separate regressions for lower-income students within each quartile of the grade 8 reading test score.

9 Supplementary Appendix

9.1 Appendix A: Notes on Simulation Calculations

To calculate the expected exposure to higher-income students for each income group under various random assignment levels, excluding own status, I do the following. I calculate the expected number of (higher-income) peers in each classroom had students been randomly assigned to classrooms in unit j. To calculate the expected number of students in each classroom, I divide the total number of student-classroom enrollments in Texas state public schools in unit j in each year-cohort $TotalEnrollments_j$ by the total number of classrooms offered in unit j (N_j). To calculate the expected number of higher-income students, I calculate the total number of student-classroom enrollments for higher-income students in unit j in each year-cohort $TotalHighIncomeEnrollments_j$ and divide it by the total number of classrooms offered in unit j (H_j). The choice of unit j depends on the random assignment level (state/district/school). This is shown in Equation (2)).

$$\begin{aligned} H_j = \frac{TotalHighIncomeEnrollments_j}{TotalClassrooms_j} \\ N_j = \frac{TotalEnrollments_j}{TotalClassrooms_j} \end{aligned} \tag{2}$$

For each student, her expected proportion of higher-income peers had students been randomly assigned to classrooms in unit j is equal to the proportion of higher-income students in unit j, i.e., $\frac{H_j}{N_j}$ adjusted to exclude the student herself. To adjust the proportion to exclude a student's own status, if a student is a higher-income student, I subtract from both the denominator and numerator her number of classroom enrollments n_{ij} during a given year in unit j. If a student is lower-income, I subtract from the denominator only her number of classroom enrollments as shown in Equations (3)) and (4)).

$$ExposureRand_{Hj} = \frac{H_j - n_{ij}}{N_j - n_{ij}} \tag{3}$$

$$ExposureRand_{Lj} = \frac{H_j}{N_j - n_{ij}} \tag{4}$$

To calculate the cumulative expected exposure for a given student across expected grades, I calculate the average of her weighted proportion of higher-income classmates across the years. The weights are based on the number of classrooms a student is enrolled in each year.

9.2 Appendix B: Segregation by Income and District School Offerings

Low exposure to upper-income students is a function of both who enrolls in a district/school and how districts and schools are organized. Two districts (or schools) could have the same proportion of upper-income students, but in one district (or school) lower-income students are exposed to fewer upper-income students because they attend different schools (or classrooms). In Figures A10 and A11, I plot the exposure of lower-income students to upper-income students in the district (or school) against the proportion of higher-income students in the district (or school).

There are districts with similar overall shares of upper-income students, yet in some of these districts, lower-income students experience schooling with far fewer upper-income peers than would be expected based on the district average, as shown in Figure A10. These districts tend to have higher levels of within district sorting between schools.

To capture within-unit (district or school) sorting by income, conditional on the proportion of upper-income students, I use the variance ratio (also known as the captures the correlation ratio and eta squared). The variance ratio the difference (gap) in exposure to higher-income students between higher- and lower-income students. If students are randomly assigned to districts, schools, and classrooms, we should expect higher- and lower-income students to have the same average number of high-income students. The variance ratio builds on the exposure measure, with a system-wide composition adjustment, as shown in Equation (5). To maintain the variance ratio interpretation of the measure being equal to 0 if students are enrolled in the same classroom, in this calculation (as done in prior literature), I include students' own income status.

$$
\begin{aligned}
VarianceRatio_j &= \frac{E[Prophighincome_{ij}|H=1] - Prophighincome_j}{1 - Prophighincome_j} \\
&= E[Prophighincome_{ij}|H=1] - E[Prophighincome_{ij}|H=0]
\end{aligned} \tag{5}
$$

The variance ratio has a straightforward interpretation. In a perfectly integrated unit, the difference in exposure to higher-income students by income status would be equal to 0. In other words, everyone would be exposed to the same proportion of higher-income students in the school $Prophighincome_j$. In a perfectly segregated school, higher-income students would only be exposed to themselves $E[Prophighincome_{ij}|H=1] = 1$, so the variance ratio would be equal to 1. Monarrez, Kisida and Chingos (2022) use the variance ratio to capture the impact of the expansion of charter schools on school segregation by race.

The variance ratio is sensitive to the unit's proportion of higher-income students: the size of the potential gap between groups differs by the units' composition (James and Taeuber, 1985). It is also sensitive to the number of classrooms/schools i within schools/districts j (Monarrez, Kisida and Chingos, 2022). A unit with more areas relative to the number of students has more scope for income sorting.

In districts with high levels of between-school sorting (top 20th percentile), lower-income students are exposed to 6.8 percentage points fewer upper-income classmates than the district average.[62] A factor that could explain differences in exposure to upper-income students, conditional on district income composition, is the number and type of schools offered. To capture the relationship between school sorting and the number and type of schools offered, for each district, I calculate the number of schools that offer a given grade level and divide it by the number of students enrolled in that grade and district in 2019. Then, I run a regression with the number of schools to students on the level of between-school sorting as the outcome of interest. To capture school heterogeneity, I split schools into three types: traditional public schools, charter schools, and private schools.[63] I only

62. I map out districts' between- and within-school sorting rates in Figure A13. I also show the average difference between observed and school and classroom integration benchmarks in Figure A12 for each district in Texas.

63. The number of private schools in the district is based on the list of schools in 2018–2019 published by the Texas Private School Accreditation Commission. This list includes the number of students enrolled in each school and the grades served by the school. However, I do not know the number of students served in each grade or their demographics. I estimate the number of students in each grade by assuming that the same number of students are served in each grade. The within- and between-school sorting measures are based on students enrolled in public schools only.

observe students enrolled in public schools (traditional and charter), and so in the case of private schools, I examine the relationship between the number of private schools and sorting between public schools. Private schools provide higher-income students with an outside option. In doing so, they can alter both the peer composition of public schools and the policies and offerings of public schools. For simplicity, I focus on students enrolled in public schools (both traditional and charter) in the 2019 academic year in Texas.

I find that districts with more charter and private schools relative to the number of students served tend to have higher levels of between-school sorting by income, as shown in Figure A14. Estimates of the relationship between the ratio of schools offered and the level of sorting by income is shown in Figure A14, with and without demographic controls. The errors are clustered at the district level and the estimates are weighted by the number of students enrolled.

The number of school options can also impact the level of within-school sorting by increasing competition for upper-income (or higher-achieving) students. Theoretically, public schools can use tracking to retain higher-performing students (Epple, Newlon, and Romano, 2002). Under tracking, higher-income students may be less likely to leave public schools to attend private schools. Figlio and Page (2002) find that higher-performing students are more likely to select into tracked schools. Similarly, Domina et al. (2017) find that schools with more advantaged students are more likely to increase tracking in response to policy pressures. As such, I run the same regression with within-school sorting as the outcome instead of between-school sorting. I find no evidence that within-school sorting in public schools is higher when the ratio of private schools to students is higher. There seems to be some evidence of a slightly lower level of within-school sorting in districts with more charter schools. These patterns are shown in Figure A15. Charter schools generally seem to have lower levels of within-school sorting, as shown in Table A2.

In schools, school composition is highly predictive of the exposure of lower-income students to upper-income peers as shown in Figure A11. That said, in schools with high levels of within-school sorting (top 20th percentile), lower-income students are exposed to 2.5 percentage points fewer upper-income classmates than the school average. Differences between schools in the level of within school sorting do not seem to be explained by differences in student test scores alone. I find that the within-school sorting by income declines by approximately 1.5 percentage points, from 11.5 to 10, when I control for students' grade 8 test scores and another 0.6 percentage points when I add an indicator for whether the student has taken Algebra I by grade 8.[64]

The number and type of courses offered in a school could impact how students are tracked by test score and income. I find that the number of science and math courses offered in a school correlates most strongly with classroom sorting by income, regardless of whether those courses are advanced. This is shown in Figure A16.[65]

9.3 Appendix C: Add Health Data and Cross-Income Friendships

The Add Health at-home survey has information on parental income but only for a random subsample of students from the wider in-school survey. Therefore, I use the socioeconomic variables available for all students to build a model that predicts student income to capture all student SESs who share the same school extracurricular. I use a simple linear regression and use the following variables to predict student income: Father and Mother's occupation, Father and Mother's education, Father and Mother's employment status, number of individuals in the household, and missing indicators. I tested and built this model within the subset of students who were surveyed at home for whom I have income data. Then, I used this model to predict the income for the entire sample of students with the in-school survey. The students were then divided into three income groups based on their predicted income that mimic the income group sizes in the Texas data.

High-SES students are those whose predicted income is in the top 24 percentiles, and low-SES students are students whose predicted income is in the bottom 29 percentiles. These three income indicators seem to effectively capture the variation in parental income. The median income is 26.6, 40.4 and 67.7 thousand dollars for low-, middle-, and high-SES students, respectively.[66] I summarize the characteristics of each of the income groups (including parental education) in Table

64. This estimate is based on regressing an indicator for student income on a student's proportion of upper-income classmates in a school. I include school and cohort-year fixed effects so that the coefficient on student income captures the difference between the proportion of upper-income students in upper-income relative to other students' classrooms in the same school. The estimates are shown in Table A4.

65. I regress the level of within-school sorting by income for high schools on the number of courses offered divided by the number of students enrolled in 2019. The within-school sorting measure is standardized based on the distribution of within-school sorting in schools weighted by the number of students enrolled. Similarly, the ratio of courses to students is standardized based on the distribution of courses to students in the sample of high schools in 2019, weighted by the number of students enrolled.

66. The median is based on the full sample of students in the at-home survey for whom I have parental income data. I list these in 1994 dollars, which are equivalent to 46.45, 70.5 and 118.21 thousand 2020 dollars. I split the set of students surveyed at home into two equally sized random groups. The in-sample half is used to build the model, and the out-of-sample half is used to test the model. The average income for out-of-sample high-SES students surveyed at home is 68.6 thousand dollars.

A1.

To identify the relationship between exposure to upper-income students and individual students' (close) cross-income friendships, I use the Add Health data. The Add Health data contain information on individual student friendship patterns and enrollment in extracurricular activities. The in-school survey asks students to list up to five male and five female friends. However, they lack information on which classrooms students are enrolled in, and as such, I use it to capture the relationship between school (and extracurricular activities) peer income composition and friendship formation. Table A3 summarizes the demographics of students in Add Health.[67] The Add Health data list 33 extracurricular activities that students can check. The extracurricular activities listed are the following: yearbook, student council, honor society, newspaper, wrestling, volleyball, track, tennis, swimming, soccer, ice hockey, football, field hockey, basketball, baseball/softball, other sport, orchestra, chorus or choir, cheerleading/dance team, band, science club, math club, history club, Future Farmers of America, drama club, debate team, computer club, book club, Spanish club, Latin club, German club, French club, other club or organization.

To capture the relationship between school (and extracurricular activities) peer income composition and friendship formation, I calculate the proportion of each student's listed friends who are high SES in the Add Health data. I define high-SES students as those in the top 24 percentiles of predicted income. Then, I calculate the proportion of a school's student population that is high-SES and the proportion of a student's peers in extracurricular activities that are high-SES (excluding herself). Last, I run a regression with the proportion of high-SES peers in school (and another with the proportion of high-SES peers in extracurriculars) on the student's proportion of high-SES friends. Relationship is shown in Figure A17.

67. I used the first wave of surveys from 1994 to 1995 that included in-school data for a sample of 85,627 students in 142 schools. I have information on friends and their SES for 77% of the students surveyed in school. For more information on how the Add Health survey was collected, see Harris et al. (2019)).

9.4 Appendix D: Tables and Figures

Table A1: Student School and Classroom Enrollment by Expected Grade

Variable	5	6	7	8	9	10	11	12
Enrolled in Charter School	.037	.057	.058	.06	.054	.058	.057	.053
	(.188)	(.232)	(.235)	(.238)	(.226)	(.235)	(.233)	(.224)
Enrolled in Alternative School	.006	.009	.011	.015	.024	.036	.045	.042
	(.08)	(.094)	(.105)	(.122)	(.153)	(.187)	(.207)	(.2)
Enrolled in Title 1 School	.706	.612	.568	.57	.418	.413	.421	.435
	(.455)	(.487)	(.495)	(.495)	(.493)	(.492)	(.494)	(.496)
Special Education	.089	.091	.09	.089	.087	.085	.083	.083
	(.285)	(.288)	(.286)	(.284)	(.281)	(.279)	(.276)	(.275)
Gifted Program	.094	.097	.099	.099	.096	.095	.098	.105
	(.292)	(.296)	(.298)	(.299)	(.294)	(.294)	(.298)	(.306)
Enrolled in Bilingual Program	.171	.08	.069	.071	.075	.078	.063	.035
	(.377)	(.271)	(.254)	(.256)	(.263)	(.268)	(.244)	(.185)
Number of Advanced Courses Taken	0	0	.001	.026	.332	.69	1.721	1.675
	(0)	(.006)	(.041)	(.237)	(.804)	(1.345)	(2.709)	(2.264)
Number of Classrooms	9.889	9.396	9.70	10.077	14.767	14.861	12.095	8.481
	(3.968)	(3.764)	(3.688)	(3.5)	(3.148)	(3.214)	(4.595)	(4.308)
Number of Courses Taken	9.277	8.632	8.806	9.288	14.167	14.333	11.695	8.232
	(3.615)	(3.32)	(3.248)	(3.112)	(2.823)	(2.868)	(4.179)	(3.906)
Any Vocational Ed	.055	.081	.207	.377	.691	.797	.832	.842
	(.229)	(.273)	(.405)	(.485)	(.462)	(.402)	(.374)	(.365)
Number of Students	1124550	1093343	1076510	1064386	1052391	1035723	988132	905982

This table describes average enrollment across three cohorts of students followed from grade 5 to 12 from 2012 to 2021 in each type of school each year as well as a description of the course offerings in each type of school. The number in brackets is the standard deviation from the mean.

Table A2: School Classroom and Course Offerings by Grade

Variable	5	6	7	8	9	10	11	12
Number of Classrooms	63.262	134.705	178.256	197.025	798.786	1001.428	909.196	615.465
	(46.286)	(83.599)	(106.223)	(119.956)	(458.365)	(528.681)	(583.499)	(454.558)
Number of Courses	10.387	17.052	24.806	31.569	137.994	208.034	232.223	193.952
	(4.177)	(7.503)	(11.134)	(12.549)	(55.622)	(78.966)	(112.296)	(106.083)
Number of Advanced Courses	0	.002	.018	.286	6.527	19.015	34.147	37.771
	(0)	(.065)	(.18)	(.749)	(5.351)	(12.55)	(22.686)	(24.838)
Number of CTE Courses	10.386	16.876	23.395	28.614	105.311	148.262	157.305	126.841
	(4.176)	(7.374)	(10.321)	(11.274)	(41.72)	(56.57)	(76.935)	(70.561)
Number of Students	144.171	285.171	314.366	315.854	556.76	510.18	479.562	445.829
	(112.186)	(149.742)	(149.736)	(153.836)	(314.335)	(289.425)	(284.642)	(268.138)
N. of Traditional Public Schools in District (weighted)	32.77	12.609	11.06	11.259	9.371	8.925	8.421	7.896
	(42.932)	(14.626)	(13.307)	(13.371)	(11.566)	(11.043)	(10.514)	(10.169)
N. of Traditional Public Schools in District (unweighted)	3.727	2.128	1.926	1.965	1.857	1.851	1.79	1.687
	(10.706)	(4.424)	(3.549)	(3.643)	(3.007)	(2.954)	(2.821)	(2.654)
Number of Schools	4263	2719	2423	2455	2309	2269	2206	2102
Number of Districts	1027	1023	1014	1013	981	979	979	979

This table summarizes the number and types of courses provided on average in schools serving students in the three cohorts in each grade level. Averages are weighted by the number of students served in each school. Numbers in brackets present the standard deviations from the mean. The average across cohorts in each grade level is based on the year a cohort is expected to be in that grade level.

Table A3: Add Health Student Summary Statistics

Variable	Mean
Hispanic	0.1190
White	0.5952
Black	0.2034
Either Parent with College Degree	0.3632
Either Parent in Prof. Occupation	0.4444
Parental Income	43.1524
Median Income	35.0000
Proportion High-SES	0.2416
Proportion Low-SES	0.2872
Number of Students	85627
Number of Schools	142

This table summarizes demographic statistics for students surveyed in the Add Health in-school surveys. The variables "Median Income" and "Parental Income" are based on the at-home surveys of a random subset of students (17,238) for whom there are income data. The high- and low-SES indicators are based on the predicted income measure described in Section 3.2. All averages are weighted by survey sampling weights to be nationally representative.

Table A4: The Role of Academic Preparation in Accounting for Within-School Differences in Exposure to Upper-Income Students

	(1)	(2)	(3)	(4)
Upper-Income	0.115	0.0997	0.0935	0.0927
	(0.0018)	(0.0016)	(0.0013)	(0.0013)
School Fixed-Effect	X	X	X	X
Cohort-Year Fixed-Effect	X	X	X	X
Grade 8 Test-Scores		X	X	X
Algebra I by G8		X	X	X
Attendance and Suspension G8				X
N	4207473	4207473	4207473	4207473
R2	0.916	0.926	0.931	0.931

The upper-income variable is an indicator variable that takes value 1 if a student is upper income. Model 1 includes school and cohortxyear fixed effects. Model 2 additionally includes test-score controls: grade 8 reading and math test scores as well as indicators for missing a test-score. Model 3 additionally includes an indicator for whether a student has taken Alegbra I by grade 8. The sample is limited to students in cohorts 2012 to 2014 (based on grade 5 entry) high-school enrollment years. Standard errors are clustered at the school level. The attendance and suspension variables are the following: number of days absent, number of member days, total suspensions (in- and out-of-school) and a missing attendance indicator. Attendance and suspension data are based on expected grade 8 school years.

Table A5: Number and Size of 9th Grade and Demographics of 9th Graders in Texas

Cohort	N. Schools	Median Size	High-Income	High-Achieve	Black	Hispanic	White
2010	1981	68	.276	.295	.14	.472	.314
2011	2067	65	.275	.277	.138	.481	.31
2012	2245	65	.26	.274	.137	.473	.293
2013	2254	68	.255	.247	.137	.481	.286
2014	2266	68.5	.255	.23	.136	.483	.288
2015	2297	71	.253	.237	.135	.491	.284
2016	2275	73	.243	.241	.136	.499	.275
2017	2264	78.5	.239	.221	.137	.502	.27
2018	2260	80	.241	.239	.137	.502	.27
2019	2309	82	.236	.259	.136	.504	.263

This table summarizes characteristics of the 2010 to 2019 9th grade cohorts. The median school size is based on equally weighting each school. The demographics are student averages weighted by the number of students enrolled.

Table A6: Grade 8 Standardized Reading Scores for 9th Graders

Cohort	% Missing	All	High-Income	Low-Income	High-Achieve
2010	7.4	.017	.384	-.246	.686
2011	8	.024	.409	-.246	.723
2012	6.8	-.011	.409	-.287	.734
2013	7.10	.082	.576	-.201	1.003
2014	8.5	-.026	.172	-.159	.907
2015	7.4	-.088	.098	-.214	.943
2016	7.6	-.198	.139	-.403	1.044
2017	8.9	.115	.564	-.13	.984
2018	7.4	-.025	.168	-.164	.925
2019	7.5	-.025	.12	-.136	.898

This table summarizes test scores of the 2010 to 2019 9th grade cohorts. The test scores are based on the grade 8 reading test and are standardized within the full population of students who took the test in a given year. "High-Achieve" students are those who scored in the top 24 percentiles of their cohort distribution of standardized test scores.

Table A7: Correlation Between Proportion Upper-Income Students in High-School and Lower-Income Students' Demographic Characteristics

	Proportion Upper-Income Students
Black Student	-0.00602
	(0.0134)
Group Mean	0.150
N Clusters	2358
N	1501742
White Student	0.0198
	(0.0134)
Group Mean	0.0900
N Clusters	2358
N	1501742
Hispanic Student	-0.00177
	(0.0186)
Group Mean	0.680
N Clusters	2358
N	1501742
Ever Immigrant	-0.0128
	(0.0114)
Group Mean	0.100
N Clusters	2358
N	1501742
Female Student	0.00186
	(0.0195)
Group Mean	0.470
N Clusters	2358
N	1501742
Income Reported on FAD	5.735
	(23.69)
Group Mean	60.27
N Clusters	2153
N	505152

Standard errors clustered at the school level in parentheses. Each coefficient is based on a regression of the variable on the proportion upper-income students, including school and cohort fixed effects, and school time trends. Ever immigrant is based on if a students was ever assigned an immigrant status in the Texas data. A student is labeled as immigrant in the data if they were not born in any state and have not attended any state for more than three academic years. Reported income is in 1000 dollars and is based on the subsample of lower income students who submit a financial aid application (34% of lower income students). The average reported income for lower-income students is much higher than the median because of a few outlier reported income; the median parent reported income for lower-income students is 20.2 thousand.

Table A8: Impact of an Increase in the Proportion of Upper-Income Students on Classroom Proportion Upper-Income Classmates for Lower-Income Students

	(1)	(2)
Proportion Upper-Income	0.592	0.603
	(0.00761)	(0.00692)
Proportion Upper-IncomeXTop G8 Test Score		0.125
		(0.00488)
Proportion Upper-IncomeXLow G8 Test Score		-0.0690
		(0.00344)
N Clusters	2322	2305
N	1369434	1249369

Standard errors are in parentheses and clustered at the school level. Coefficients are based on Equation (1). The regressions include the full sample of lower-income students. The second model includes an interaction with students who scored in the top 80th percentile and bottom 20th percentile based on their grade 8 reading test scores. Models include cohorts 2011–2019 because classroom data are only available starting 2011. The outcome is a student's classroom proportion of high-income peers.

Table A9: Impact of an Increase in the Proportion of Higher-Income Students on a Cohort's Racial/Ethnic Composition

	(1)	(2)	(3)
	Prop. Hispanic	Prop. Black	Prop. White
Proportion Upper-Income	-0.240	-0.0545	0.323
	(0.0131)	(0.00802)	(0.0126)
N Clusters	2358	2358	2358
N	1501742	1501742	1501742

Standard errors are in parentheses and clustered at the school level. The coefficients are based on Equation (1). Models include cohorts 2010–2019.

Table A10: Impact of an Increase in the Proportion of Upper-Income Students on Number of Advanced Courses Offered

	(1)	(2)
	Advanced Courses Offered	AP Courses Offered
Proportion Upper-Income	0.529	0.163
	(0.575)	(0.350)
Group Mean	10.895	6.122
N Clusters	2358	2358
N	1501742	1501742

Standard errors are in parentheses and clustered at the school level. Coefficients are based on Equation (1). Sample includes lower income students in cohorts 2010–2019. Averages capture the number of advanced and AP courses offered in a given year in a school.

Table A11: Impact of Proportion Upper-Income and High-Achieving Students on College Enrollment for Lower-Income Students

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Enrolled in College/University						
Proportion Upper-Income	0.0918		0.127	0.0555		0.0907
	(0.0224)		(0.0226)	(0.0210)		(0.0210)
Proportion High-Achieve		-0.103	-0.117		-0.146	-0.152
		(0.0189)	(0.0187)		(0.0162)	(0.0161)
Group Mean	0.370					
Enrolled in a Public 2yr College						
Proportion Upper-Income	0.125		0.146	0.0460		0.0706
	(0.0238)		(0.0239)	(0.0223)		(0.0228)
Proportion High-Achieve		-0.0536	-0.0702		-0.101	-0.106
		(0.0181)	(0.0178)		(0.0158)	(0.0161)
Group Mean	0.290					
Enrolled in a Public 4yr College						
Proportion Upper-Income	0.0340		0.0561	0.0491		0.0705
	(0.0142)		(0.0139)	(0.0156)		(0.0155)
Proportion High-Achieve		-0.0674	-0.0738		-0.0876	-0.0927
		(0.0137)	(0.0135)		(0.0126)	(0.0125)
Group Mean	0.140					
Enrolled in a Selective University						
Proportion Upper-Income	0.00752		0.0131	0.00699		0.0125
	(0.00397)		(0.00412)	(0.00470)		(0.00482)
Proportion High-Achieve		-0.0170	-0.0185		-0.0228	-0.0237
		(0.00358)	(0.00363)		(0.00444)	(0.00448)
Group Mean	0.0200					
School Time Trends				X	X	X
N	1501742	1501742	1501742	1501742	1501742	1501742
N Clusters	2358	2358	2358	2358	2358	2358

Standard errors are in parentheses and clustered at the school level. Coefficients are based on Equation (1). Models (1)–(3) do not include school time trends. College enrollment outcomes include cohorts 2010–2019. Models (3) and (6) include both the proportion of upper-income and higher-achieving peers in the cohort. Group Mean is the average for lower-income students in the sample.

Table A12: Impact of Proportion Upper-Income and High-Achieving Students on College Graduation and Wages for Lower-Income Students

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Graduated College/University						
Proportion Upper-Income	0.0541		0.0605	0.0249		0.0311
	(0.0213)		(0.0211)	(0.0229)		(0.0229)
Proportion High-Achieve		-0.0148	-0.0222		-0.0163	-0.0194
		(0.0191)	(0.0191)		(0.0175)	(0.0177)
Group Mean	0.170					
Wage 2023						
Proportion Upper-Income	3190.6		3700.9	4337.8		5141.6
	(1409.3)		(1425.5)	(1670.4)		(1689.0)
Proportion High-Achieve		-1320.7	-1774.2		-2938.7	-3451.1
		(985.0)	(987.6)		(1079.5)	(1084.9)
Group Mean	20490.5					
Income Percentile 2023						
Proportion Upper-Income	1.879		3.020	3.560		4.412
	(1.363)		(1.383)	(1.620)		(1.638)
Proportion High-Achieve		-3.597	-3.967		-3.315	-3.778
		(1.009)	(1.013)		(1.062)	(1.064)
Group Mean	46.75					
School Time Trends				X	X	X
N	700245	700245	700245	700245	700245	700245
N Clusters	1992	1992	1992	1992	1992	1992

Standard errors are in parentheses and clustered at the school level. Coefficients are based on Equation (1). Models (3) and (6) include both the proportion of upper-income and higher-achieving peers in the cohort. College graduation and wages include cohorts 2010–2014. Group Mean is the average for lower-income students in the sample.

Table A13: Impact of Proportion Upper-Income Conditional on Peer Achievement: Sensitivity to Measure of Achievement

	Model 1	Model 2	Model 3	Model 4	Model 5
Enrolled in College/University					
Proportion Upper-Income	0.0639	0.0833	0.0947	0.0459	0.0759
	(0.0211)	(0.0206)	(0.0211)	(0.0194)	(0.0207)
Group Mean	0.370				
Enrolled in a Public 2yr College					
Proportion Upper-Income	0.0548	0.0666	0.0720	0.0380	0.0594
	(0.0222)	(0.0220)	(0.0230)	(0.0213)	(0.0224)
Group Mean	0.290				
Enrolled in a Public 4yr College					
Proportion Upper-Income	0.0513	0.0655	0.0757	0.0391	0.0627
	(0.0157)	(0.0154)	(0.0156)	(0.0142)	(0.0154)
Group Mean	0.140				
Enrolled in a Selective University					
Proportion Upper-Income	0.00728	0.0103	0.0140	0.00731	0.00958
	(0.00476)	(0.00473)	(0.00486)	(0.00464)	(0.00475)
Group Mean	0.0200				
Graduated College/University					
Proportion Upper-Income	0.0460	0.0474	0.0306	0.0336	0.0325
	(0.0226)	(0.0225)	(0.0230)	(0.0227)	(0.0229)
Group Mean	0.170				
Average Quarterly Wage 2023					
Proportion Upper-Income	5318.9	5502.0	5258.4	5422.3	4742.6
	(1669.2)	(1669.5)	(1690.2)	(1703.2)	(1678.8)
Group Mean	20490.5				
Income Percentile 2023					
Proportion Upper-Income	4.268	4.513	4.481	4.678	4.073
	(1.618)	(1.624)	(1.641)	(1.655)	(1.629)
Group Mean	46.75				
Proportion High-Achieving (Math G8)	X				
Proportion High-Achieving (Math+Reading G8)		X			
Proportion High-Achieving (Reading G3-G8)			X		
Proportion High-Achieving (Reading G3)				X	
Peer Average Std. Test Score (Reading G8)					X

Standard errors are in parentheses and clustered at the school level. Coefficients are based on Equation (1). College enrollment outcomes include cohorts 2010–2019 (N: 1501742; N Clusters: 2358). College graduation and wages include cohorts 2010–2014 (N: 700245; N Clusters: 1992). All models include both a peer achievement control. The measure of achievement varies across models. Models (1)–(4) include a control for the proportion high-achieving peers where high-achieving students are those who score in the top quarter of the standardized test score distribution. Model (4) controls for students' own grade 3 reading and math test-scores instead of grade 8. Model (5) controls for a continuous measure of average grade 8 reading scores for all students. Group Mean is the average for lower-income students in the sample.

Table A14: Impact of an Increase in the Proportion of Upper-Income Students on Lower-Income Students, Conditional on Racial/Ethnic Composition

	(1) Any College	(2) 2yr Public	(3) 4yr Public	(4) Selective	(5) Grad Any	(6) Wage 2023	(7) Income Percentile
Proportion Upper-Income	0.0595	0.0473	0.0513	0.00831	0.0259	4613.0	3.712
	(0.0218)	(0.0231)	(0.0160)	(0.00476)	(0.0234)	(1693.9)	(1.655)
Proportion Hispanic Students	0.0180	0.0117	0.0124	0.00421	0.00694	1213.9	0.796
	(0.0173)	(0.0169)	(0.0111)	(0.00306)	(0.0167)	(1268.5)	(1.264)
Proportion Black Students		-0.00888	-0.0299	-0.0164	0.00394	-0.0380	-489.2
-0.456							
	(0.0298)	(0.0269)	(0.0194)	(0.00517)	(0.0245)	(1894.2)	(1.864)
N Clusters	2358	2358	2358	2358	1992	1992	1992
N	1501742	1501742	1501742	1501742	700245	700245	700245

Standard errors are in parentheses and clustered at the school level. The coefficients are based on Equation (1) but controlling for the sharing of Black and Hispanic students in the cohort (excluding own race/ethnicity). Models (1)–(4) include cohorts 2010–2019. Models (5)–(7) include cohorts 2010–2014.

Table A15: Impact of an Increase in the Proportion of Higher-Income Students on Lower-Income Students within a Racial/Ethnic Group: Hispanic Students

	(1) Any College	(2) 2yr Public	(3) 4yr Public	(4) Selective	(5) Grad Any	(6) Wage 2023	(7) Income Percentile
Proportion Upper-Income Hispanic Students	0.122	0.0952	0.0877	0.0203	0.0391	6162.9	4.542
	(0.0655)	(0.0781)	(0.0523)	(0.0139)	(0.0690)	(4137.8)	(4.015)
N Clusters	2220	2220	2220	2220	1885	1885	1885
N	1017112	1017112	1017112	1017112	475618	475618	475618

Standard errors are in parentheses and clustered at the school level. The coefficients are based on Equation (1). Models (1)–(4) include cohorts 2010–2019. Models (5)–(7) include cohorts 2010–2014. The sample is limited to Hispanic lower-income students.

Table A16: Impact of an Increase in the Proportion of Higher-Income Students on Lower-Income students within a Racial/Ethnic Group: White students

	(1) Any College	(2) 2yr Public	(3) 4yr Public	(4) Selective	(5) Grad Any	(6) Wage 2023	(7) Income Percentile
Proportion Upper-Income White Students	0.0629	0.0526	0.0339	0.00564	0.0159	11145.9	14.54
	(0.0407)	(0.0398)	(0.0259)	(0.00990)	(0.0468)	(3591.0)	(3.640)
N Clusters	1980	1980	1980	1980	1668	1668	1668
N	131812	131812	131812	131812	60843	60843	60843

Standard errors are in parentheses and clustered at the school level. The coefficients are based on Equation (1). Models (1)–(4) include cohorts 2010–2019. Models (5)–(7) include cohorts 2010–2014. The sample is limited to White lower-income students.

Table A17: Impact of an Increase in the Proportion of Higher-Income Students on Lower-Income Students within a Racial/Ethnic Group: Black Students

	(1) Any College	(2) 2yr Public	(3) 4yr Public	(4) Selective	(5) Grad Any	(6) Wage 2023	(7) Income Percentile
Proportion Upper-Income Black Students	0.0800	-0.0810	0.487	0.0657	0.213	2928.2	-8.320
	(0.165)	(0.155)	(0.124)	(0.0389)	(0.178)	(14220.2)	(10.90)
N Clusters	1756	1756	1756	1756	1390	1390	1390
N	228839	228839	228839	228839	106733	106733	106733

Standard errors are in parentheses and clustered at the school level. The coefficients are based on Equation (1). Models (1)–(4) include cohorts 2010–2019. Models (5)–(7) include cohorts 2010–2014. The sample is limited to Black lower-income students.

Table A18: Impact of Proportion of Upper-Income, Holding Constant Proportion Mid-Income Students, on Lower-Income Students

	(1) Any College	(2) 2yr Public	(3) 4yr Public	(4) Selective	(5) Grad Any	(6) Wage 2023	(7) Income Percentile
Proportion Upper-Income	0.0198	0.0109	0.0312	0.00567	0.0248	5483.6	5.291
	(0.0230)	(0.0240)	(0.0169)	(0.00501)	(0.0253)	(1773.8)	(1.730)
Proportion Middle-Income	-0.0657	-0.0646	-0.0330	-0.00254	-0.00338	2059.4	3.170
	(0.0195)	(0.0200)	(0.0111)	(0.00310)	(0.0176)	(1095.8)	(1.106)
Group Mean	0.370	0.290	0.140	0.0200	0.170	20490.5	46.75
N Clusters	2358	2358	2358	2358	1992	1992	1992
N	1501742	1501742	1501742	1501742	700245	700245	700245

Standard errors are in parentheses and clustered at the school level. Coefficients are based on Equation (1) including a control for the share of middle income students in the cohort. The sample is limited to lower-income students. Models (1)–(4) include cohorts 2010–2019 and Models (5)–(7) include cohorts 2010–2014.

Table A19: Bounding the Estimated Impact of the Share of Upper-Income Peers on Wage in 2023 Using Between School Variation

	Model 1	Model 2	Model 3
Proportion Upper-Income	4130.8	5182.8	5171.2
	(500.3)	(453.7)	(611.5)
Group Mean	20490.5	20490.5	20490.5
N Clusters	1995	1994	1995
N	700248	699831	700248
Cohort Fixed Effect	X	X	X
G8 School-Cohort Fixed Effect		X	
District Fixed Effect			X
School Fixed Effect			

Standard errors are in parentheses and clustered at the school level. Models include cohorts 2010-2014. Income for students without unemployment insurance data are imputed with 0. All models include cohort fixed effects and control for student grade 8 test-score and demographic characteristics. Model (2) include school grade 8 and cohort in grade 8 school fixed effects based on students' first school in grade 8 enrollment prior to enrolling grade 9. Model (3) includes district fixed effects.

Table A20: Limiting the Sample to Schools with Standard Deviation in the Share of Upper-Income Peers Within its 95% CI Based on Simulations of Random Deviation from the School Mean: Impact of Increase in Proportion Upper-Income Students

	(1) Any College	(2) 2yr Public	(3) 4yr Public	(4) Selective	(5) Grad Any	(6) Wage 2023	(7) Income Percentile
Proportion Upper-Income	0.0461	0.0484	0.0379	0.00162	0.0222	3769.1	3.851
	(0.0225)	(0.0232)	(0.0154)	(0.00497)	(0.0258)	(1954.0)	(1.873)
N clusters	2147	2147	2147	2147	1796	1796	1796
N	1223685	1223685	1223685	1223685	565673	565673	565673

Standard errors are in parentheses and clustered at the school level. The coefficients are based on Equation (1) but without controlling for students grade 8 test and demographic characteristics. Models (1)–(4) include cohorts 2010–2019 and Models (5)–(7) include cohorts 2010–2014. Models exclude observations from schools with a deviation from school mean trend in the share of upper-income peers outside the 95% confidence interval of likely deviations from the school mean based on a simulated distribution of deviations from the school mean discussed in more details in Section 6.2.

Table A21: Impact of Increase in Proportion Upper-Income Students on Lower-Income Students: Income Defined by Free/Reduced Lunch Status Before High School

	Any College	2yr Public	4yr Public	Selective	Grad Any	Wage 2023	Income Percentile
Proportion of Upper-Income Students	0.0665	0.0543	0.0462	0.0150	0.0279	2219.5	2.122
	(0.0180)	(0.0195)	(0.0122)	(0.00390)	(0.0167)	(1174.6)	(1.160)
Group Mean	0.380	0.300	0.150	0.0200	0.170	20634.2	47.96
N clusters	2358	2358	2358	2358	1992	1992	1992
N	1940788	1940788	1940788	1940788	1097186	1097186	1097186

Standard errors are in parentheses and clustered at the school level. The coefficients are based on Equation (1) but with a slightly different definition of income. Lower and upper-income students are defined as students who are always and never on free/reduced lunch status before high-school. Models (1)–(4) include cohorts 2010–2019 and Models (5)–(7) include cohorts 2010–2014.

Table A22: Proportion Upper-Income Peers and Lower-Income Students' Average Cohort Income

	Prop FAD	Parent Income (FAD)	Years FRPL	Prop FRPL
Proportion Upper-Income	0.252	112.1	-6.695	-0.795
	(0.0165)	(20.65)	(0.105)	(0.0109)
Group Mean	0.380	94.24	6.400	6.400
N	1501742	1496651	1501742	1501742
N clusters	2358	2271	2358	2358

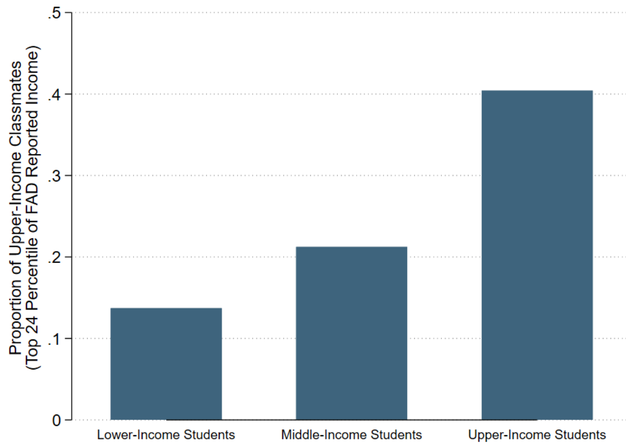
Standard errors clustered at the school level in parentheses. Each coefficient is based on a regression of the variable on the proportion upper-income students, including school and cohort fixed effects, and school time trends. The outcomes capture a lower-income students' average cohort characteristics excluding own status. "Prop FAD" captures the proportion of a student's cohort who submitted their financial aid (FAD) applications. "Parent Income (FAD)" is the average cohorts' income based on students' reported parental income in their FAD application. Years FRPL captures a student's peers average number of years on free/reduced lunch and prop. FRPL captures a student's peers average proportion of years on free/reduced lunch.

Table A23: Impact of Proportion Upper-Income Students on Lower-Income Students' College Enrollment and wages: Robustness to Specification

	Model 1	Model 2	Model 3	Model 4	Model 5
Enrolled in College/University					
Proportion Upper-Income	0.143	0.0783	0.0787	0.0555	0.0585
	(0.0248)	(0.0209)	(0.0205)	(0.0210)	(0.0229)
Group Mean	0.370	0.370	0.370	0.370	0.370
N Clusters	2358	2358	2358	2358	2355
Enrolled in a Public 2yr College					
Proportion Upper-Income	0.164	0.0630	0.0630	0.0460	0.0310
	(0.0253)	(0.0221)	(0.0218)	(0.0223)	(0.0254)
Group Mean	0.290	0.290	0.290	0.290	0.290
N Clusters	2358	2358	2358	2358	2355
Enrolled in a Public 4yr College					
Proportion Upper-Income	0.0634	0.0625	0.0630	0.0491	0.0480
	(0.0153)	(0.0153)	(0.0151)	(0.0156)	(0.0169)
Group Mean	0.140	0.140	0.140	0.140	0.140
N Clusters	2358	2358	2358	2358	2355
Enrolled in a Selective University					
Proportion Upper-Income	0.0121	0.00900	0.00916	0.00699	0.00903
	(0.00400)	(0.00470)	(0.00470)	(0.00470)	(0.00577)
Group Mean	0.0200	0.0200	0.0200	0.0200	0.0200
N Clusters	2358	2358	2358	2358	2355
Graduated College/University					
Proportion Upper-Income	0.0612	0.0394	0.0385	0.0249	0.0350
	(0.0208)	(0.0227)	(0.0226)	(0.0229)	(0.0276)
Group Mean	0.170	0.170	0.170	0.170	0.170
N Clusters	1992	1992	1992	1992	1991
Wage 2023					
Proportion Upper-Income	4076.4	5304.4	5289.4	4335.1	3751.5
	(1500.9)	(1732.4)	(1735.5)	(1669.9)	(2245.7)
Group Mean	20490.5	20490.5	20490.5	20490.5	20490.5
N Clusters	1992	1992	1992	1992	1991
Income Percentile 2023					
Proportion Upper-Income	2.966	4.567	4.586	3.556	3.461
	(1.444)	(1.700)	(1.704)	(1.619)	(2.233)
Group Mean	46.75	46.75	46.75	46.75	46.75
N Clusters	1992	1992	1992	1992	1991
Linear School Time Trends		X	X	X	X
Student Demographic Controls			X	X	X
Student G8 Test Controls				X	X
Grade 8 School-Cohort Fixed Effects					X
Proportion High-Achieving Students					

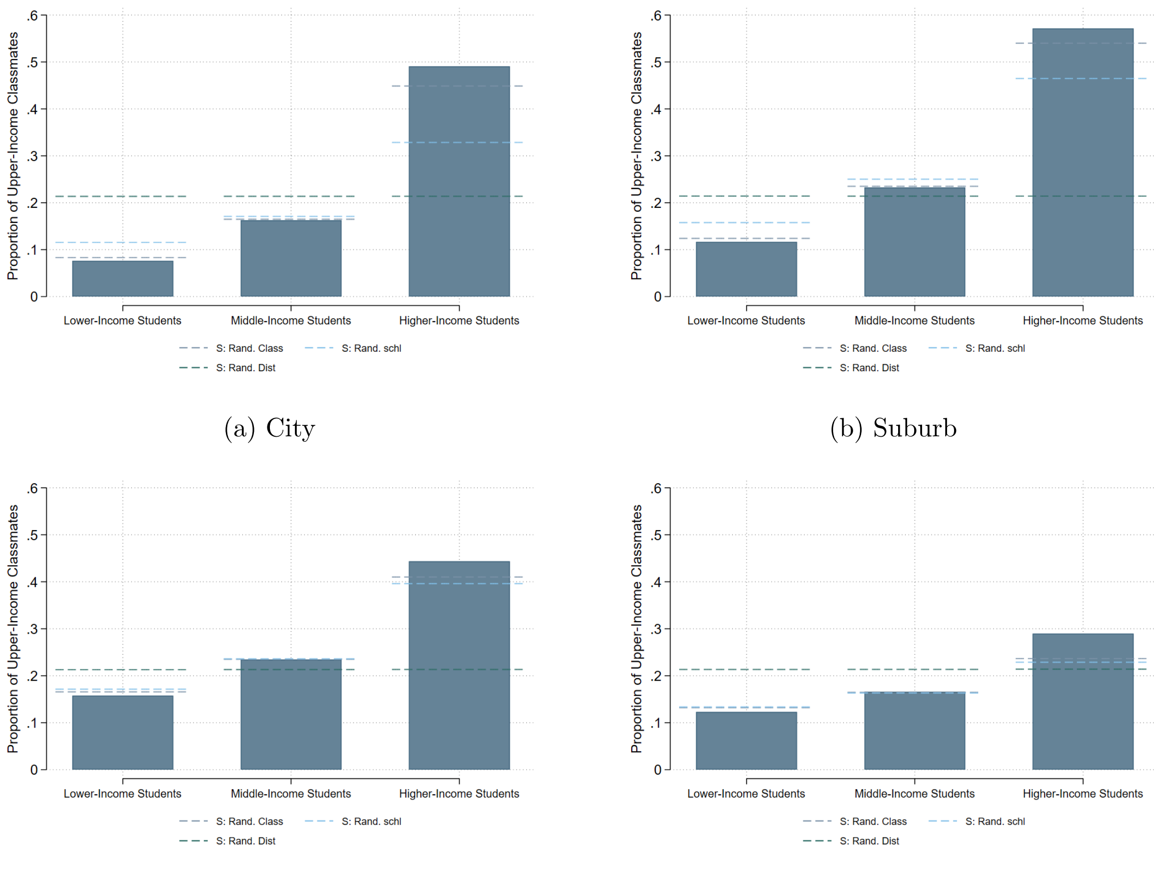
Standard errors are in parentheses and clustered at the school level. Coefficients are based on Equation (1). All models include cohort and school fixed effects. College enrollment outcomes include cohorts 2010–2019, and graduation and wages outcomes include cohorts 2010–2014. Group Mean is the average for lower-income students in the sample. Student demographic controls include student own race, immigrant status and gender. Student grade 8 test controls include their grade 8 math and reading scores and an indicator for missing grade 8 math and reading tests.

Figure A1: Exposure to Higher-Income students is Defined by Parental Income Reported in their Financial Aid Application



Notes: Parental income is based on parental gross adjusted income listed on the financial aid application. There may be students with parental income equivalent to this or higher but who have not applied for financial aid. Exposure to higher-income students is calculated by dividing the total number a student's classmates between grades 5 and 12 with parental income in the top 24 percentiles based on the distribution of parental income in the financial aid data is divided by the total number of classmates with financial aid data. Lower- middle- and upper-income students on the x-axis are defined by proportion of years in free/reduced lunch status.

Figure A2: Exposure to Higher-Income Students by District Type: Observed Relative to Random Assignment



(a) City

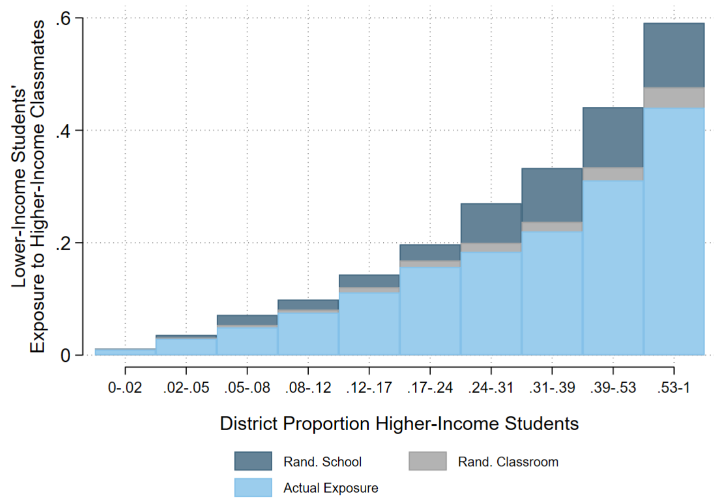
(b) Suburb

(c) Rural

(d) Town

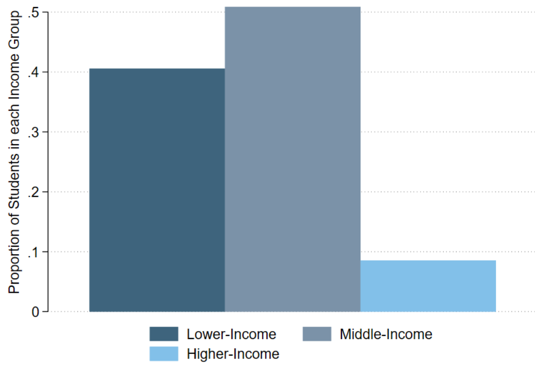
Notes: Similar to Figure 2 but split students by district type. Students are assigned district type based on the district they enroll in grade 5. District type is based on NCES categorization of districts.

Figure A3: The Percentage Point Gap in Exposure to Higher-Income Students Increases as the Proportion of Higher-Income students in the District Increases

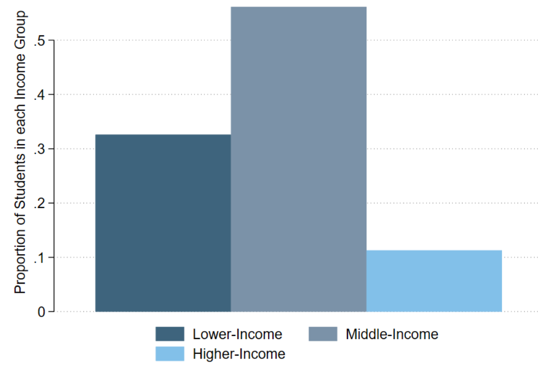


Notes: This plot presents lower-income students' exposure to higher-income students in districts with various proportions of higher-income students. Exposure is defined as the average proportion of higher-income classmates in a year. The light blue bar shows the observed proportion of higher-income students in lower-income students' classrooms. The navy bar presents the expected proportion of higher-income students had students been randomly assigned to schools in the district: school integration benchmark. The gray bar presents the expected proportion of higher-income students had students been randomly assigned to classrooms in the school: classroom integration benchmark. Districts are split into ten percentiles based on the distribution of the proportion of higher-income students in the district in a given school-year. The distribution is weighted by the number of students in each district (independent of income status). The lower and upper bound for each of the percentiles is shown on the x-axis.

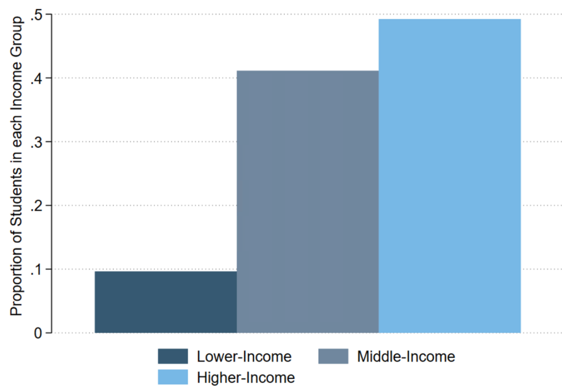
Figure A4: Distribution of Parental Income by Race/Ethnicity



(a) Hispanic Students



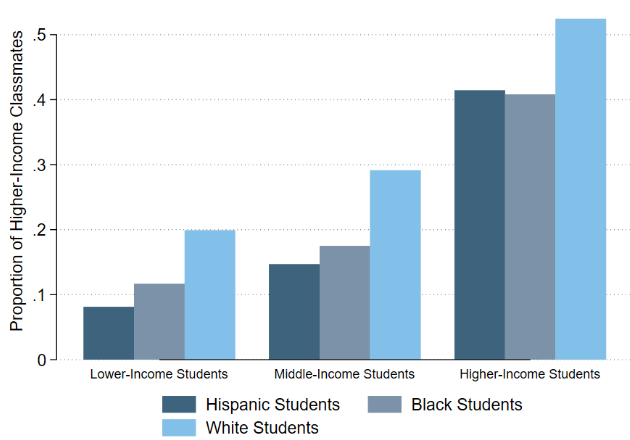
(b) Black Students



(c) White Students

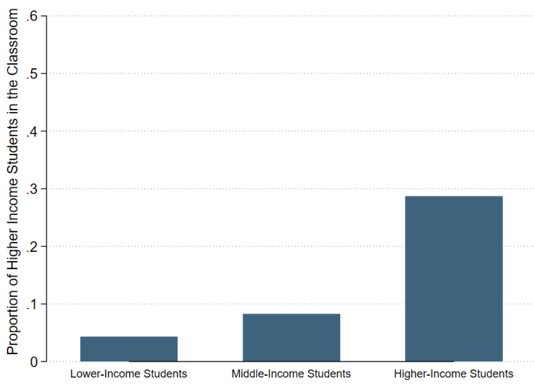
Notes: This plot captures the average proportion of students in each income level, for each racial/ethnic group across three cohorts. The average is weighted by the number of students across three cohorts in each racial/ethnic group.

Figure A5: Gap in Exposure to Higher-Income Students Exists Independent of Students' Race/Ethnicity

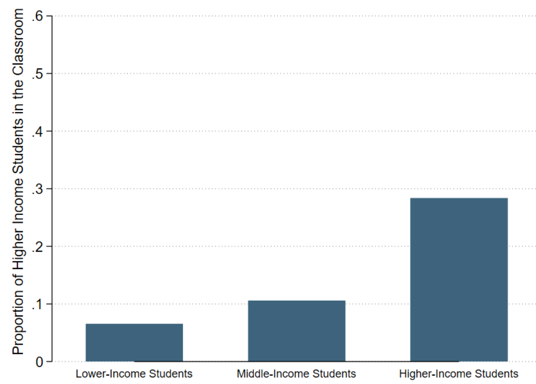


Notes: This plot captures the proportion of higher-income classmates across grades 5 to 12 for each income and racial/ethnic group. Higher-income students are defined as students never on free/reduced lunch.

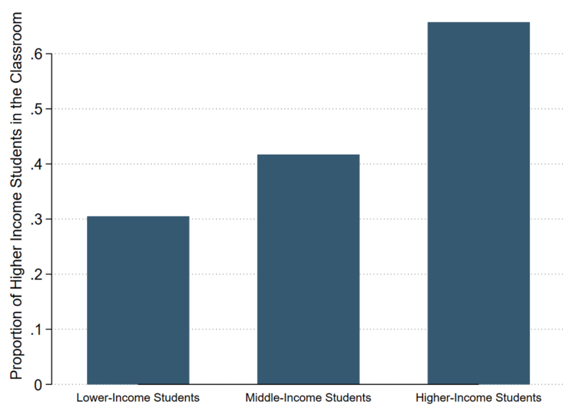
Figure A6: Proportion of Higher-Income, Same-Race/Ethnicity Classmates



(a) Hispanic Students



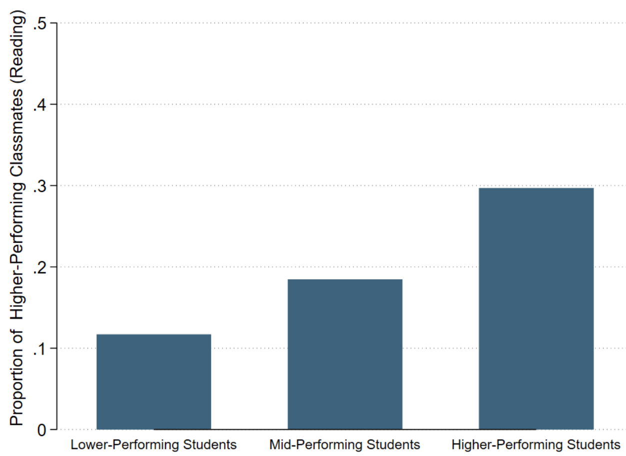
(b) Black Students



(c) White Students

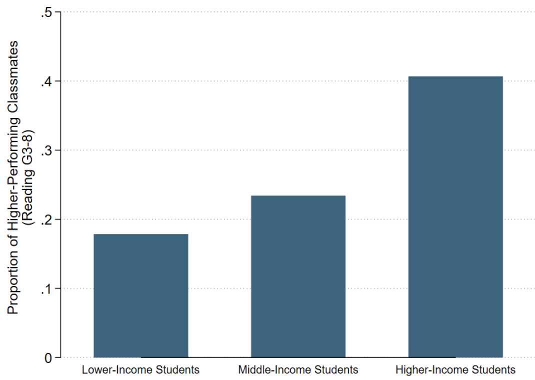
Notes: These plots capture the proportion of higher-income classmates of the same race/ethnicity across grades 5 to 12 for each income and racial/ethnic group. The average is weighted by the number of students across three cohorts in each racial/ethnic group.

Figure A7: The Cross-Test-Score Exposure Gap is Smaller than the Cross-Income Exposure Gap

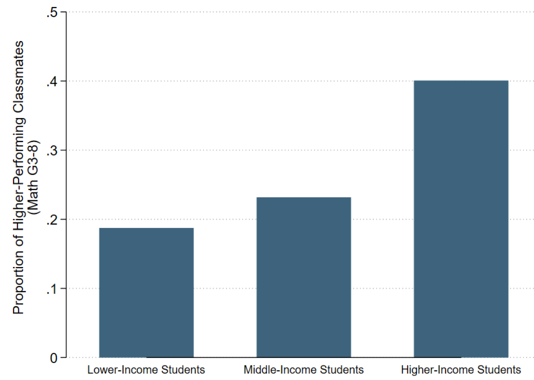


*Notes:*This plot captures students' cumulative proportion of higher-performing classmates between grade 5 and expected grade 12. I define higher-performing students as students who performed in the top 24 percentiles of the test score based on the grade 4 standardized reading test. The test score is standardized based on the raw score for all students who have taken the test in a given year. The percentile is based on the distribution of students who have a grade 4 test score. Approximately 5% of students are missing grade 4 reading test scores. I impute students' missing test score with 0 (i.e., the average test-score because the test score is standardized). Lower-achieving students are those who performed in the bottom 29 percentiles of grade 4 test scores.

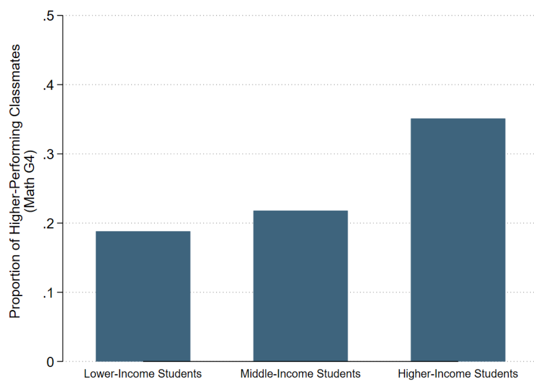
Figure A8: Consistent Gap in Share of Higher-Achieving Students Across Achievement Definitions



(a) Average Grades 3 to 8 Reading Test



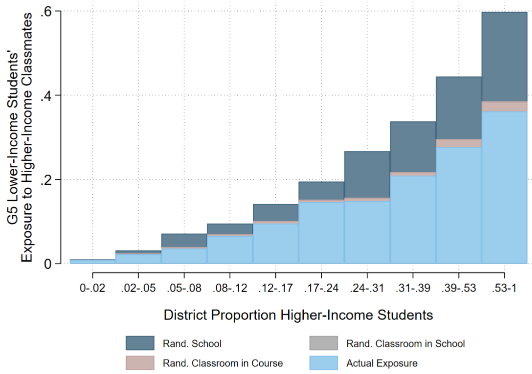
(b) Average Grades 3 to 8 Math Test



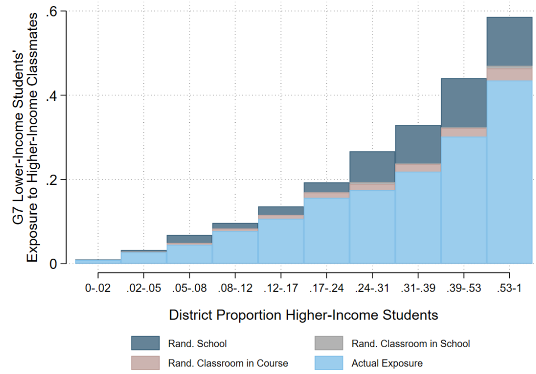
(c) Math G4 Test

Notes: Plots capture the average cumulative proportion of total classmates that are higher-achieving by student income. All tests are standardized within year-grade. High achieving students are those who are in the top 24 percentiles of the average grades 3 to 8 standardized tests (or grade 4 test in panel (c)). Cumulative exposure based on following three cohorts of grade 5 students (2012-2014) to expected grade 12.

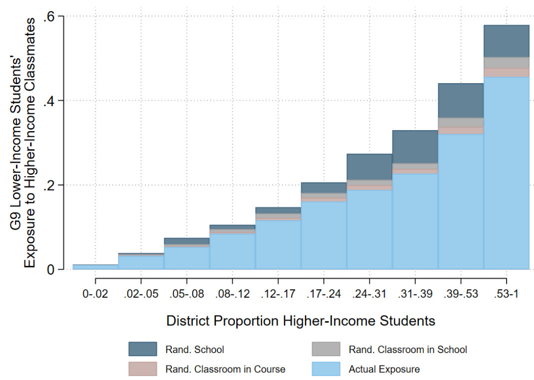
Figure A9: Classroom Accounts for More of the Gap in Exposure in Grade 9 than in Earlier Grades



(a) Grade 5



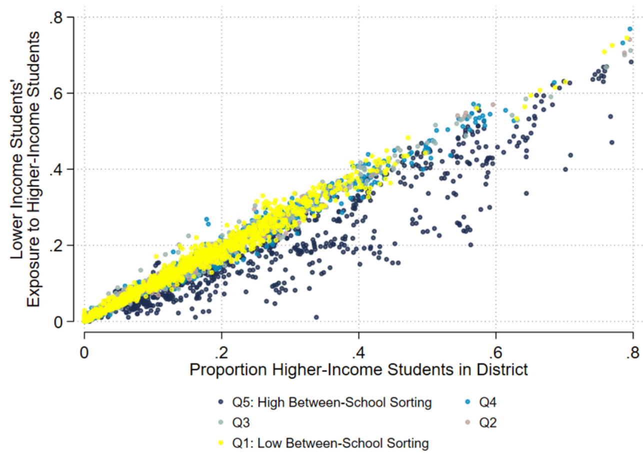
(b) Grade 7



(c) Grade 9

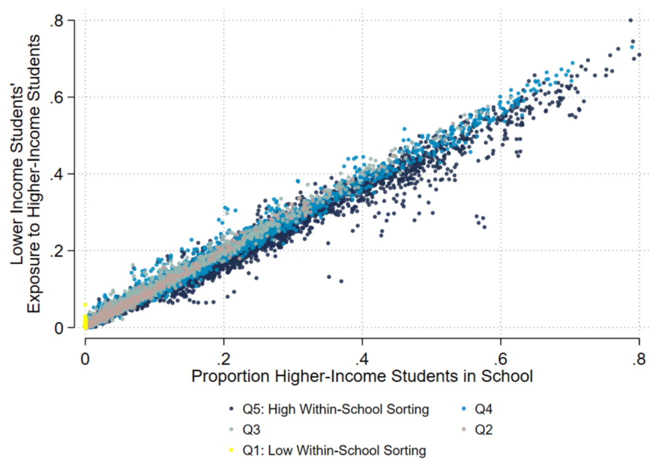
Notes: This plot presents lower-income students' exposure to higher-income students in districts with various proportions of higher-income students. Exposure is defined as the average proportion of higher-income classmates in a year. The light blue bar shows the observed proportion of higher-income students in lower-income students' classrooms. The navy bar presents the expected proportion of higher-income students had students been randomly assigned to schools in the district: school integration benchmark. The gray bar presents the expected proportion of higher-income students had students been randomly assigned to classrooms in the school: classroom integration benchmark. The pink bar presents the expected proportion of higher-income students had students been randomly assigned to classrooms in a course in a school. Districts are split into ten percentiles based on the distribution of the proportion of higher-income students in the district in a given school-year. The distribution is weighted by the number of students in each district (independent of income status). The lower and upper bound for each of the percentiles is shown on the x-axis. The panels present the gap by expected grade.

Figure A10: Conditional on District Composition, Lower-Income Students' Exposure to Higher-Income Classmates



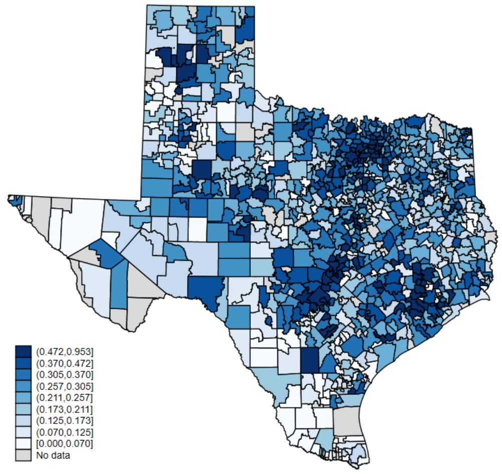
Notes: Each dot represents a district-grade. I only include districts with more than 50 lower-income students enrolled in a grade across three cohorts. The darker color represents district-grades with more sorting between schools, while the lighter dots represent district-grades with less sorting between schools. Sorting is captured by the variance ratio.

Figure A11: Conditional on School Composition, Lower-Income Students' Exposure to Higher-Income Classmates

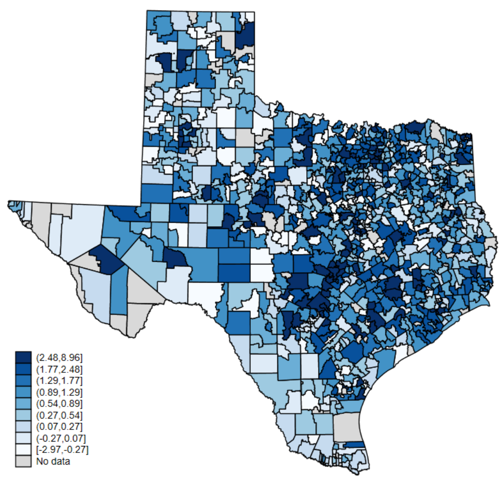


Notes: Each dot represents a school-grade. I only include schools with more than 50 lower-income students enrolled in a grade across three cohorts. The darker color represents school-grades with more sorting within school, while the lighter dots represent school-grades with less sorting within schools. Sorting is captured by the variance ratio.

Figure A12: Observed Exposure Relative to Exposure Under Random Assignment



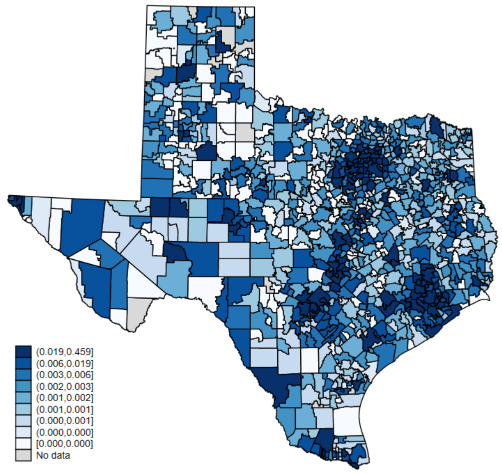
(a) Relative to Random Assignment to Schools and Classrooms within Districts



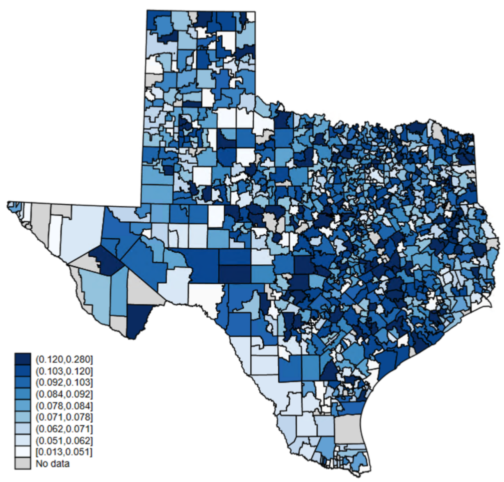
(b) Relative to Random Assignment to Classrooms within Schools

Notes: This plot is limited to lower-income students. Lower-income students are students always on free/reduced lunch. The units used are percentages. The plot captures the percentage-point difference between the observed proportion of higher-income students to whom lower-income students are exposed and the expected proportion of higher-income students had students been randomly assigned to classrooms within the district. The maps are constructed by grouping school districts into 9 deciles and shading the areas so that lighter colors correspond to lower difference in observed and simulated exposure. Areas with fewer than 10 higher- or lower-income students are shaded in grey under the "No-data" category. Figure (a) captures the percentage-point difference between the observed proportion of higher-income students to whom lower-income students are exposed and the expected proportion of higher-income students had students been randomly assigned to schools and classrooms within the district. Figure (b) captures the percentage point difference between the observed proportion of higher-income students to whom lower-income students are exposed and the expected proportion of higher-income students had students been randomly assigned to classrooms within the district.

Figure A13: Level of Sorting by Income Within and Between Schools in a District



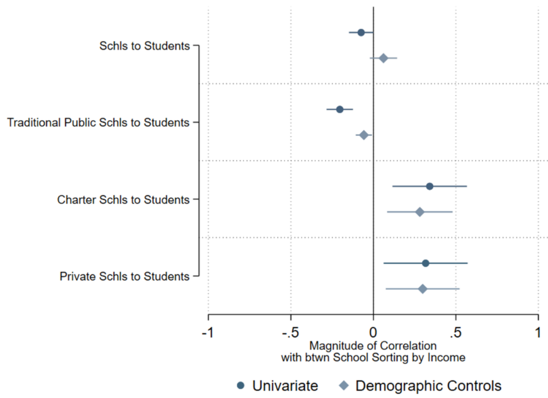
(a) Variance Ratio between Schools



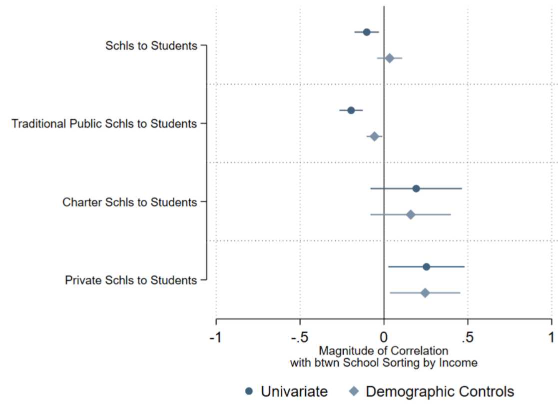
(b) Variance Ratio within Schools

Notes: Panel (a) captures within-district sorting across schools by income. It is the difference in the proportion of higher-income students in higher- relative to other-income student schools, within the same district. Panel (b) captures within-school sorting across classrooms. The line of best fit is weighted by the number of students enrolled across cohorts in each expected grade level. It is the difference in the proportion of higher-income students in higher- relative to other-income student classrooms, within the same school.

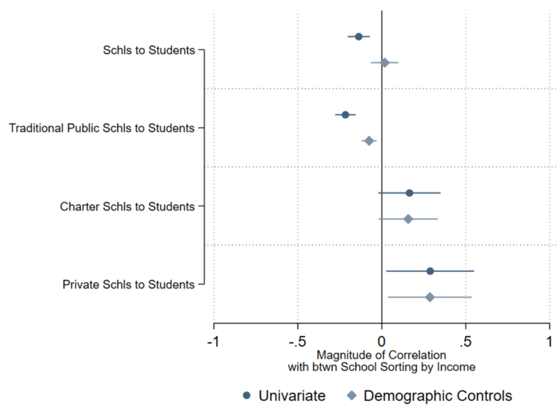
Figure A14: Between-School Sorting in Public Schools is Higher in Districts with More Charter and Private School Options



(a) Grades 3 to 5



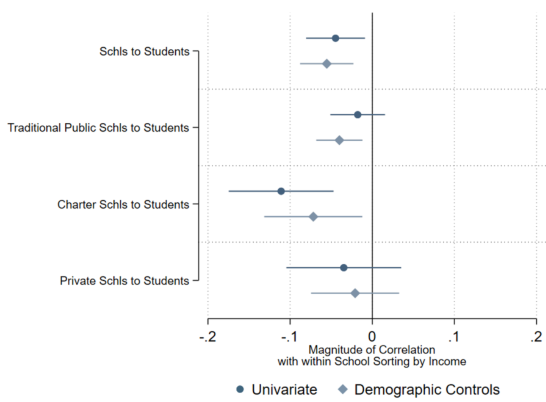
(b) Grades 6 to 8



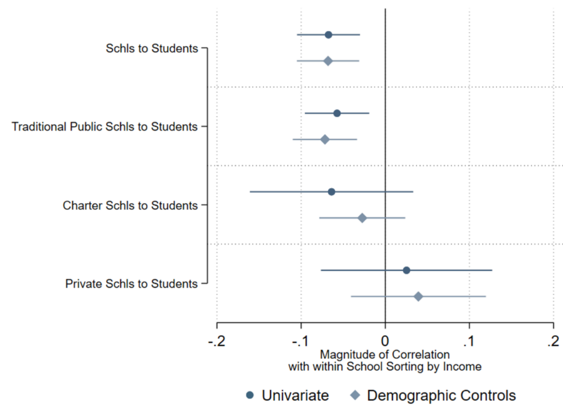
(c) Grades 9 to 12

Notes: Both the number of schools to students and the variance ratio are standardized based on the school-to-student distribution and variance ratio in a district, weighted by the number of students enrolled and calculated within the grade group. Schools are placed into districts, and the ratio is calculated as the number of schools in the district to the number of students served in the district in 2019. The number of private schools, number of students and number of grades served in each private school are based on the Texas Alliances Accredited Private Commission archive data for the 2018–2019 school year. The "univariate" estimate is based on regressing the variance ratio on the standardized number of schools to students. The "demographic controls" estimate is based on regressing the variance ratio on the standardized number of schools to students, with controls for the proportion of Black, Hispanic and higher-income students in the district.

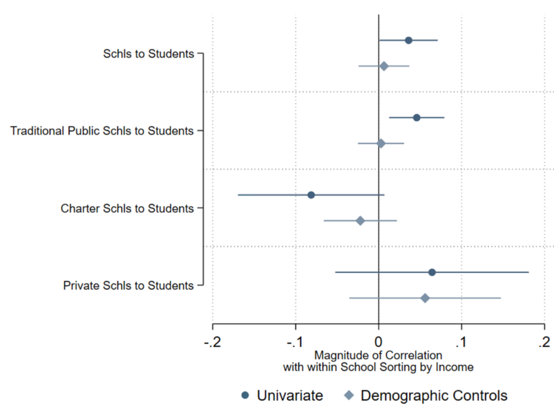
Figure A15: No Strong Evidence of an Association between Within-School Sorting in Public Schools and Number of School Options



(a) Grades 3 to 5



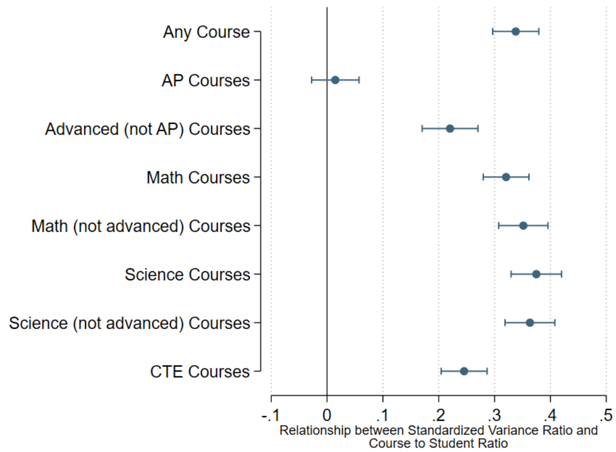
(b) Grades 6 to 8



(c) Grades 9 to 12

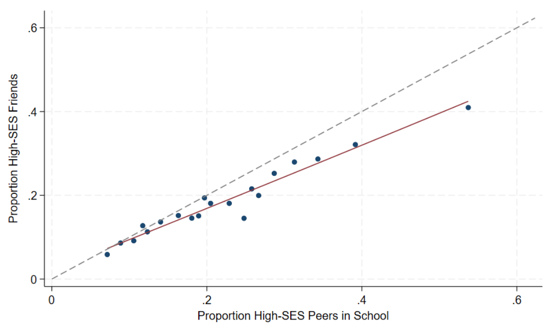
Notes: Similar to Figure A14 but with the within-school variance ratio (sorting) as the outcome.

Figure A16: Within-School Sorting Correlates More with the Number of Science and Math Courses than Advanced Courses

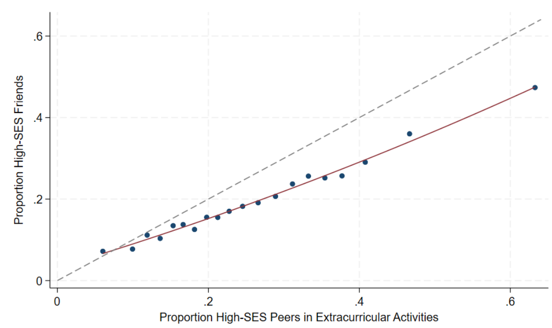


Notes: Based on 2019 high school classroom enrollment data. The first row captures the school-level univariate regression coefficient from regressing the standardized sorting measure on the standardized number of courses offered to students served. The other rows capture the correlation with other specific groups of courses to students served. Math courses capture the number of any math course to the number of students served, standardized. Math (not advanced) courses capture all math courses that are not advanced to the number of students served. The standardization is based on the weighted distribution of courses to students and within-school sorting across schools. The correlation is weighted by the number of students enrolled in a school. The 95% confidence intervals are presented. The standard errors are clustered at the school level.

Figure A17: Strong Relationship Between Students' School and Extracurricular Composition and Friendship Pattern



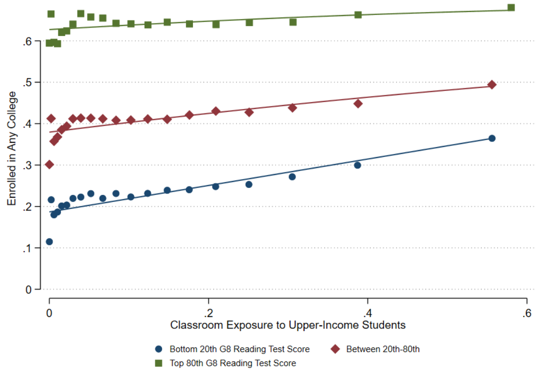
(a) Proportion of High-SES Peers in School



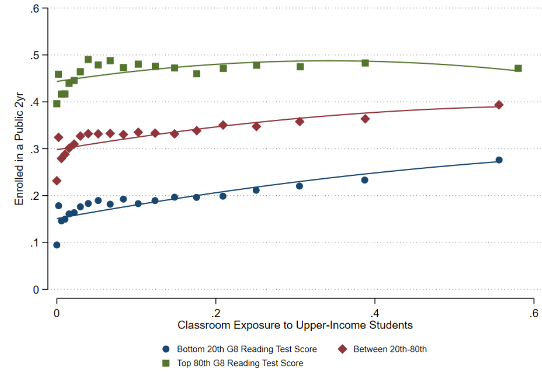
(b) Proportion of High-SES Peers in School Extracurricular Activities

Notes: The definition of high-SES is described in Section 3.2. The binned scatter plots are based on the full sample of low-SES students with data on friendship patterns. The bins are based on grouping the x-values into 20 equal-sized bins. Then, it computes the average y-variable value for each bin. The fitted lines are weighted by survey sampling weights. Panel (a) captures the relationship between a student's proportion of high-SES peers in school and their proportion of high-SES friends. Panel (b) captures the relationship between a student's proportion of high-SES peers in their school-listed extracurricular activities and their proportion of high-SES friends. In both panels, the dashed line is a 45-degree line representing a 1-to-1 relationship between the average proportion of high-SES students in school/extracurriculars and the average proportion of high-SES friends.

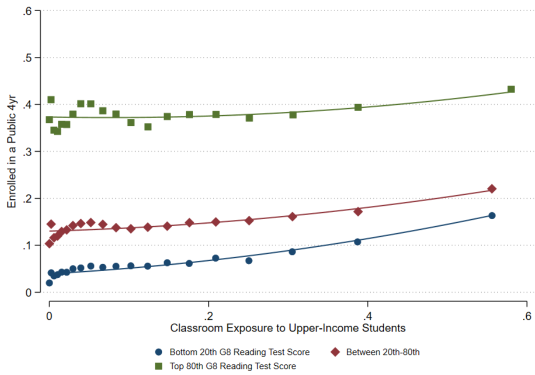
Figure A18: Exposure to Higher-Income Students, College Enrollment and Employment



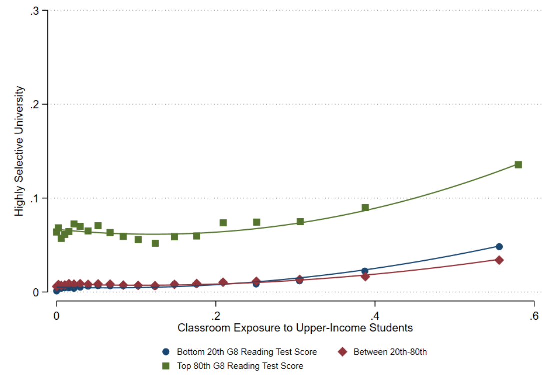
(a) Enrolled in Any College



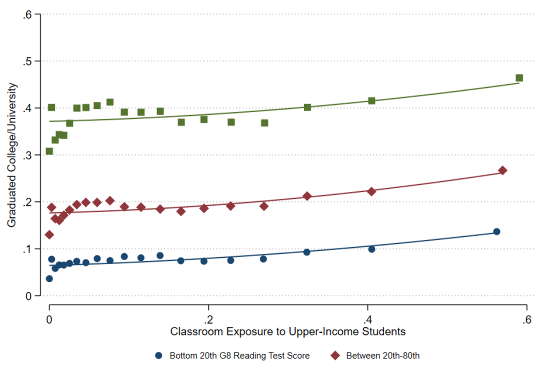
(b) Enrolled in 2-year Public College



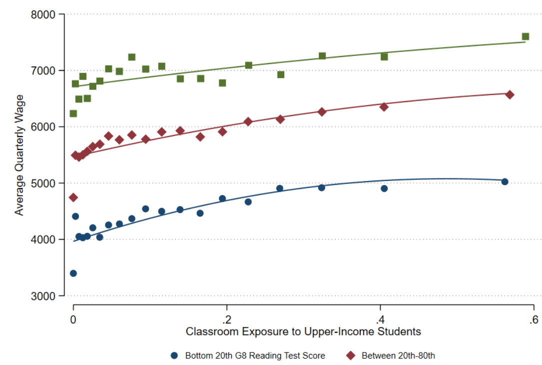
(c) Enrolled in 4-year Public University



(d) Enrolled in Highly Selective University



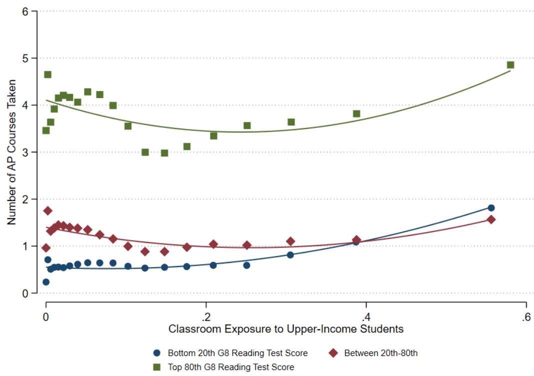
(e) Graduated from Any College/University



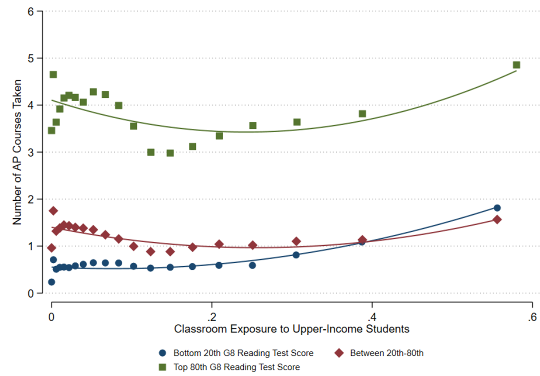
(f) Average Quarterly Wage in 2023 (Age 22-28)

Notes: The binned scatter plots are based on lower-income students and present the raw observational relationship (with no controls) between classroom exposure to upper-income students in high school and college enrollment and wages. Students are placed into three groups based on their standardized grade 8 reading test score: students who scored in the top 80th, between 20th and 80th, and 20th percentile of the cohort test score distribution. Test scores are standardized within the full sample of students who had taken the grade 8 test in a given year—92% of the students in the sample have grade 8 reading test scores. College enrollment outcomes include cohorts 2011 to 2019. College graduation and wage outcomes include cohorts 2011 to 2014. The bins are based on grouping the x-values into 20 equal-sized bins. Then, it computes the average y-variable value for each bin.

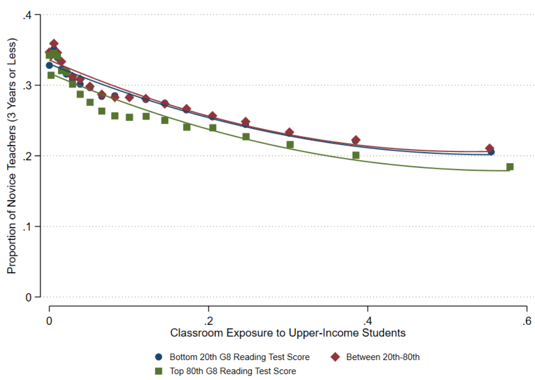
Figure A19: Exposure to Higher-Income Students and School Resources



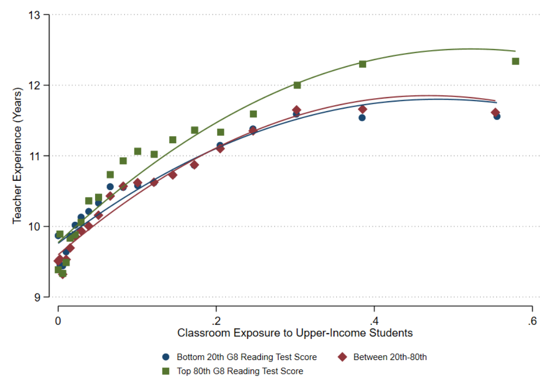
(a) Number of AP Courses Enrolled in



(b) Number of Advanced Courses Enrolled in



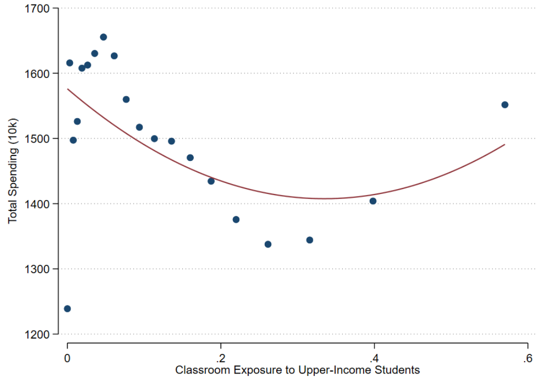
(c) Proportion of Novice Teachers



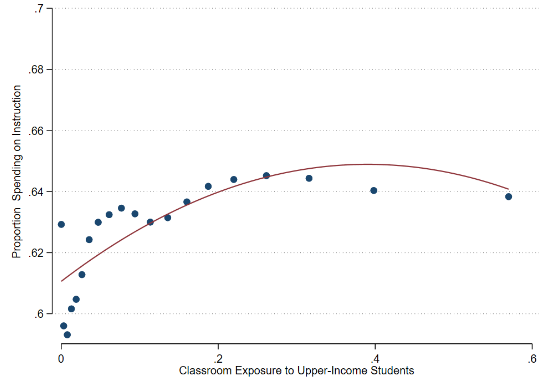
(d) Years of Teacher Experience

Notes: The line and plots are similar to those in Figure (A18). AP and advanced course enrollments are based on the average number of AP courses taken by the student during high school. The course enrollment outcomes include cohorts 2011 to 2019. The proportion of novice teachers is based on the proportion of full-time teachers with three or less years of experience that taught in a student's classroom in high school. Teacher data include cohorts 2012 to 2019.

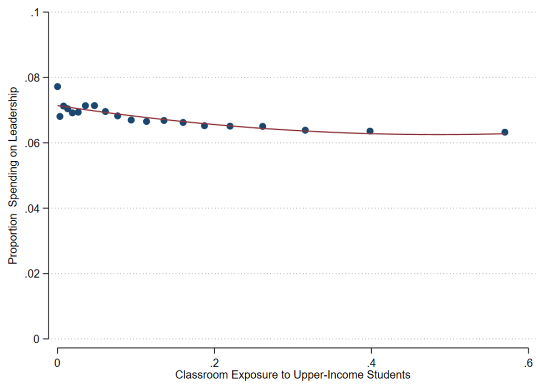
Figure A20: Exposure to Higher-Income Students and School Spending per Pupil



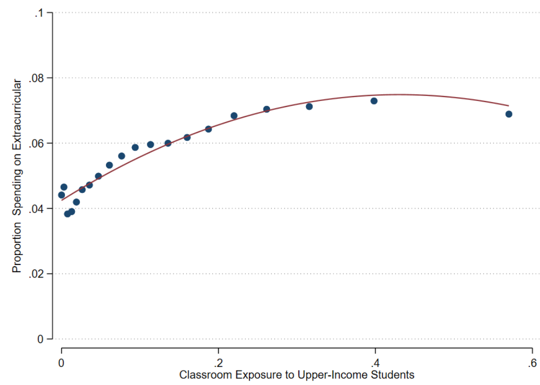
(a) Average School Spending per Pupil



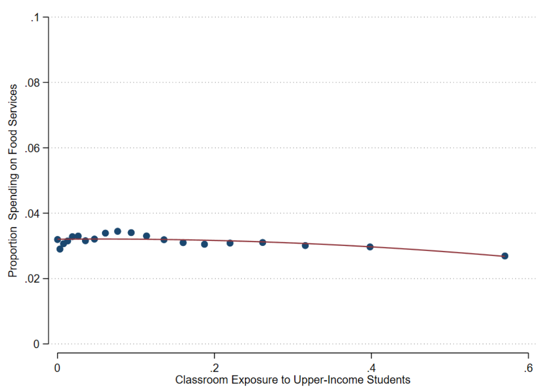
(b) Proportion of Total Spending on Instruction



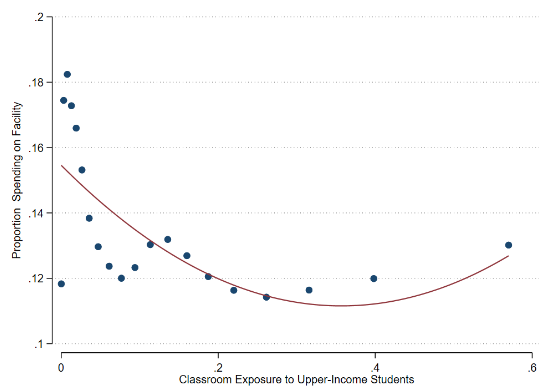
(c) Proportion of Total Spending on School Counselors/Extracurriculars



(d) Proportion of Total Spending on Co-



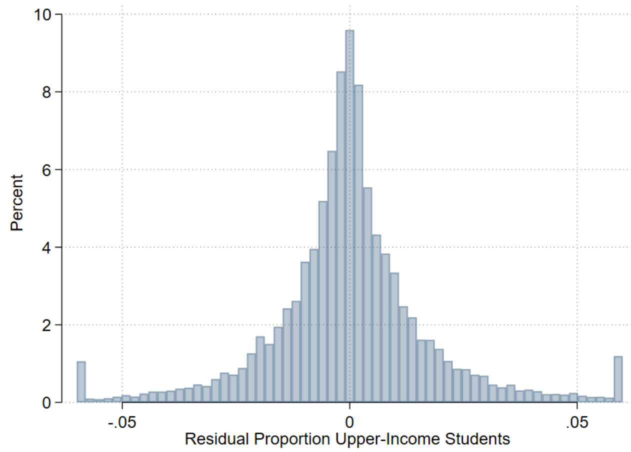
(e) Proportion of Total Spending on Food Services



(f) Proportion of Total Spending on Facilities

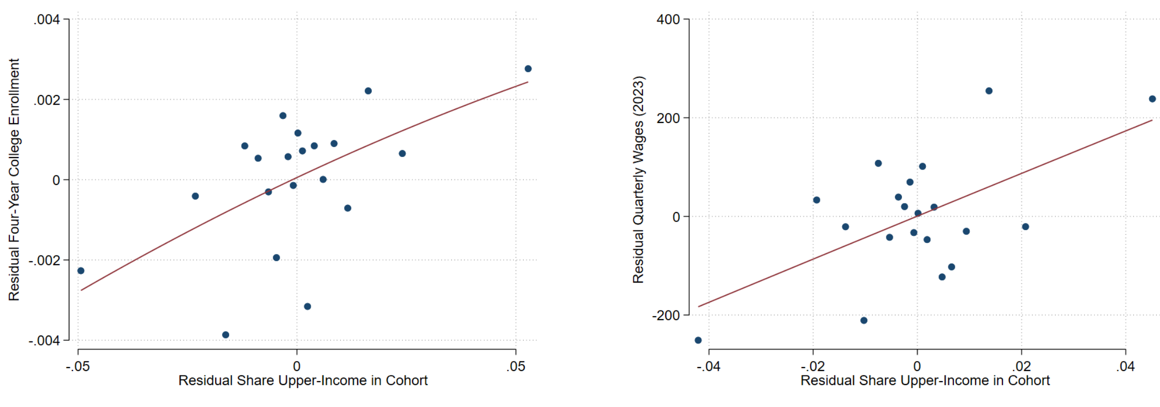
Notes: Spending is based on school actual spending data between 2012 and 2019 in each year divided by the total number of students enrolled in the school that year. Panel (a) captures the average yearly spending per pupil during the cohort's high-school years. Panels (b)–(f) capture the proportion of total spending on each category. The instruction category combines the following functions: instruction, instruction resources and media services, curriculum and staff development, and instructional leadership. Facilities combines the following functions: facility acquisition and construction and facility maintenance/operations. With the exception of food services, I only included categories that make up more than 4% of the budget, on average. The data include cohorts 2012 to 2019. The bins are based on grouping the x-values into 20 equal-sized bins. Then, it computes the average y-variable value for each bin.

Figure A21: Distribution of Residual Variation in Proportion Upper-Income Students



Notes: The histogram presents the variation in the proportion of upper-income students based on the residual from a regression with school and cohort fixed effects, as well as school time trends.

Figure A22: Linearity of the Relationship between Residual College Enrollment and Wages and Share of Upper-Income Students

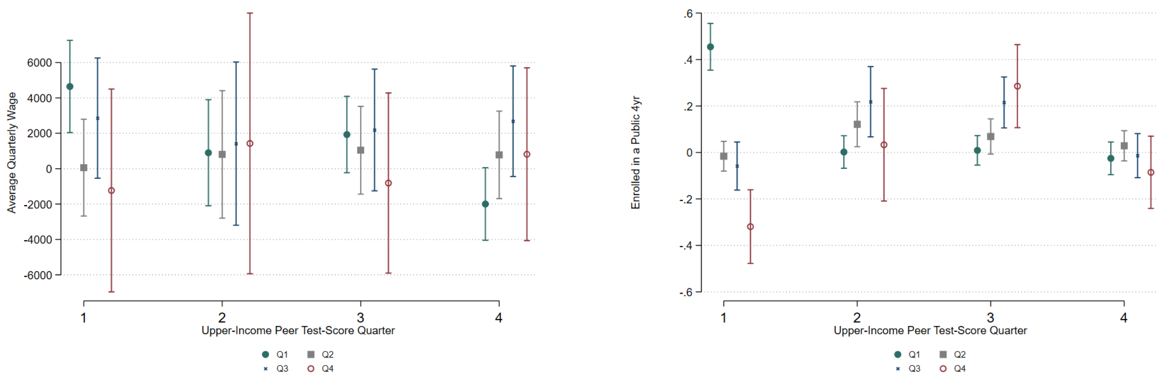


(a) Residual Four-Year College Enrollment

(b) Residual Wages

Notes: Residuals based on running a regression with each of the share of upper-income students and outcomes (college enrollment and wages) on school fixed effects, cohort fixed effects and school-trends as well as student characteristics. The binned scatter plots are based on the full sample of lower income students in cohorts 2010 to 2019. The bins are based on grouping the x-values into 20 equal-sized bins.

Figure A23: Impact of Having a Higher Share of Upper-Income Students by Achievement



(a) Average Quarterly Wage (2023)

(b) Four-Year College Enrollment

Notes: The figure displays the estimated impact of exposure to upper-income peers, disaggregated by the upper-income peers' grade 8 reading test score quartiles. The coefficients are obtained from four separate regressions, each restricted to lower-income students within a given achievement group: top 25% (>75th percentile), upper-middle (50th–75th), lower-middle (25th–50th), and bottom 25% (<25th percentile) of the grade 8 reading test score distribution.